THE BUILT ENVIRONMENT AND HEALTH: A SPATIAL ANALYSIS OF TYPE 2 DIABETES AND CHILDHOOD WEIGHT STATUS IN URBAN NEW ZEALAND

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“An ounce of prevention is worth a pound of cure”

- Benjamin Franklin, 1736

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Ruia, ruia, tahia, tahia,

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Abstract

The built environment is an integral aspect of everyday life. It provides the context in which individual behaviours are set and can affect both individual and population health. It is shaped by distal systematic drivers which influence demographic and epidemiological changes such as the globalisation of economic processes, urbanisation, mechanisation, changing agricultural and trade policies, and dietary transitions. These systematic drivers, in turn, influence local environments which act as proximal determinants of population outcomes. Subsequently, the contextual impact of the local built environment is considered to be an influential aspect of spatial disparities in population health outcomes.

The focus of this thesis is on health outcomes of high weight status in children and population level Type 2 Diabetes Mellitus (T2DM). The prevalence of these health issues has increased alongside societal, demographic and cultural changes. While there are various biological, behavioural and environmental risk factors which influence the development of these health issues there is still much to be learned about both direct and indirect causes. The overall aim of this thesis is to analyse the built environment in urban New Zealand and investigate associations with the spatial epidemiology of two health outcomes, high weight status in children and population level T2DM.

Despite substantial research and significant public attention directed toward these health issues within Aotearoa New Zealand, there are still critical gaps in the spatial understanding of such health outcomes. Current literature also highlights a lack of research which focuses on T2DM. This thesis addresses such research gaps using an ecological approach to analysis which utilises Geographic Information Systems (GIS) and spatial epidemiological methods. This is the first study in New Zealand to spatially quantify the effects of multiple environmental exposures on health outcomes of both high weight status in children and population level T2DM, for all urban areas, using a geospatial approach. It establishes novel measures of the built environment using data on fast food outlets, takeaways, dairy/convenience stores, supermarkets, fruit and vegetable stores, physical activity facilities, and greenspace to assess potential associations between contextual factors and health outcomes. In the context of this study, the former three of these categories are considered unhealthy exposures and detrimental to overall health. The latter four categories, in contrast, are considered to be healthy exposures and health-promoting.

This thesis has, in turn, made original contributions to the current body of knowledge by: (1) including the use of both established and novel approaches to measuring various aspects of the built environment, and (2) analysing spatial data on health outcomes of high weight status in children and population level T2DM for all urban areas of New Zealand and assessing potential associations with the built environment. Such analysis also provides the opportunity to assess how the built environment may relate to not only outcomes of multiple chronic health conditions, but also different population groups.

When considering relationships between measures of the built environment and socioeconomic deprivation, results of this study indicate that accessibility to both and unhealthy and healthy exposures is generally higher in the most deprived areas compared to the least deprived areas. This study also found some notable results when looking at the spatial distribution of both high weight status in children and population level T2DM, finding that T2DM is more spatially clustered than high weight status in children. Both health outcomes were also shown to be heavily influenced by demographic factors and associated with accessibility to environmental exposures. Interestingly, results show that both of these health issues may be more heavily influenced by health-promoting resources than those considered detrimental to health. Health-promoting resources were shown to have a consistently positive effect on both health outcomes, while those considered detrimental to health showed varying, and largely insignificant, associations. Caution must be exercised, however, to ensure that a balanced approach is taken within prevention efforts which addresses environmental factors as well as economic accessibility, individual behaviours and societal norms.

The current study has implications for both policy and future research efforts as a deeper knowledge of local environments forms a basis on which to better understand spatial associations between the built environment and health as well as formulate policy directed toward environmental influences on chronic health conditions. It is vital to consider such contextual influences in order to better understand the spatial epidemiology of chronic health conditions in Aotearoa New Zealand. Accounting for these contextual influences within both research and policy can not only enhance understandings of such health concerns, but can also identify opportunities for prevention efforts. This thesis has, in turn, provided insight into such associations and a base from which to further address the complexities of such issues using a geospatial approach.

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Name: Simon Kingham Signature: S. Kingham Date: 26 Feb 2019

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Glossary

Acronym	Description
ACR	Urinary albumin/creatinine ratio
AIC	Akaike Information Criterion
API	Application Programming Interface, Google
B4SC	Before (B4) School Check
BIC	Bayesian Information Criterion
BMI	Body Mass Index
CAR	Conditional Autoregressive
CI	Credible Interval
DALY(s)	Disability Adjusted Life Years
DHB	District Health Board
DIC	Deviance Information Criterion
d.p.	Decimal Place
E2SFCA	Enhanced Two-Step Floating Catchment Area [model]
ESDA	Exploratory Spatial Data Analysis
FCP	Food Control Programme
FSP	Food Safety Programme
GIS	Geographic Information Systems/Geographic Information Science
GLM	Generalised Linear Model
GLMM	Generalised Linear Mixed Model
GP	General Practitioner
High weight status	Ratio of body weight to height squared, BMI overweight/obese
HbA1c	Haemoglobin A1c[1]
ID	International Dollars[2]
IDF	International Diabetes Federation
IGT	Impaired Glucose Tolerance
IMD	Index of Multiple Deprivation
INFORMAS	International Network for Food and Obesity/NCD Research, Monitoring and Action Support

[1] Measures blood glucose over the previous 8 – 12 weeks, reflecting the average plasma glucose (sugar in bloodstream) and measuring how much has become stuck to red blood cells

[2] ID would purchase in any given country a comparable amount of services that a USD dollar would within the United States

Glossary … continued

LCDB	Land Cover Database
LINZ	Land Information New Zealand
MALA	Metropolis adjusted Langevin algorithm
MAUP	Modifiable Areal Unit Problem
MCMC	Markov Chain Monte Carlo
mmol/mol	millimoles per mole
MoH	Ministry of Health (New Zealand)
MPI	Ministry for Primary Industries
NCDs	Non-communicable Disease(s)
NHI	National Health Index
NZD	New Zealand Dollars
NZDep	New Zealand Deprivation Index
NZHS	New Zealand Health Survey
NZPHC	New Zealand Parliament Health Committee
PHE	Public Health England
PHO	Primary Healthcare Organisation
QQ plot	Quantile-Quantile plot
R	R, statistical software
SES	Socioeconomic status
SMR	Standardised Morbidity Ratio
StatsNZ	Statistics New Zealand
T1DM	Type 1 Diabetes Mellitus
T2DM	Type 2 Diabetes Mellitus
TA	Territorial Authority, based on city or district council
VDR	Virtual Diabetes Register
VIF	Variance Inflation Factor
WHO	World Health Organisation

Chapter 1 : Introduction

It has been theorised that economies predicated on consumption-based growth have led to an increase in chronic health conditions due to an associated over-consumption of energy dense, low-nutrient foods (Swinburn et al., 2011). Such effects have been exacerbated by a decrease in physical activity due to the sedentary nature of contemporary lifestyles and urban sprawl. Thus, variations in chronic health outcomes have arisen as a product of interactions between global food systems, local environments, and individual behaviours. Research on this topic has emerged from multiple disciplines including geography, epidemiology, public health, and urban planning and is therefore shaped by a multiplicity of theoretical and methodological approaches (Mavoa, Thornton & Coffee, 2019). Of increasing relevance are Geographic Information Systems (GIS), which enable the visualisation and analysis of spatial information to better understand such relationships. Despite substantial research being published on chronic health conditions such as obesity and diabetes, and significant public attention being garnered toward these health issues, there are critical gaps in the spatial understanding of such health conditions within Aotearoa New Zealand.

Overall, the purpose of this chapter is to provide an introduction to this thesis. It begins by discussing the research context within Aotearoa New Zealand, followed by the research gap which this thesis aims to address. Next, it discusses the thesis aims and objectives and the research approach. An outline of the thesis structure is then given to conclude the chapter.

1.1 Research context

The start of the 21st century saw a significant change in Aotearoa New Zealand, spurred on by rising non-communicable diseases and chronic health conditions, as morbidity overtook mortality as the primary cause of health loss (Ministry of Health 2016a). This is referred to as the disability transition and is a product of industrialisation, urbanisation, and improved public health and medical technologies (Ministry of Health, 2016a; World Health Organization [WHO], 2002). The New Zealand Ministry of Health investigated these relationships, finding that approximately one million Disability Adjusted Life Years (DALYs) are lost in New Zealand each year, with 88% of health loss caused by non-communicable diseases and chronic health conditions (Ministry of Health, 2016a).

Many specific conditions contribute to health loss within New Zealand, including both Type 2 Diabetes Mellitus (T2DM) and high weight status. High weight status is defined by a ratio of body weight to height squared (Biing-Hwan, 2005), and is commonly classified into categories of overweight and obese which are characterised by high amounts of adipose tissue, or body fat, in relation to body mass. Overweight and obesity are typically measured by Body Mass Index (BMI), with classifications of BMI $\geq 25\ kg/m^2$ and $\geq 30\ kg/m^2$ respectively (WHO, 2014). The term high weight status will be used throughout this thesis to represent the combination of both overweight and obese BMI categories. Notably, high weight status is a prominent risk factor for a range of chronic health conditions, particularly T2DM, as excess body weight increases insulin resistance resulting in high blood glucose levels (Kahn, Utzschneider & Hull, 2006). T2DM, in turn, is a chronic disease which occurs when the pancreas is not producing enough insulin, which regulates blood sugar, or becomes resistant to and cannot effectively use the insulin it produces (International Diabetes Federation [IDF], 2015).

Results from the 2015/16 New Zealand Health Survey (NZHS) show both ethnic and economic disparities in rates of T2DM and high weight status in New Zealand (Ministry of Health, 2016b). Research has also shown a clear relationship between rates of T2DM and increasing age, with at least one in six of those aged 65 and over diagnosed with diabetes in 2015 (Ministry of Health, 2015). This is a particularly important consideration for both population health and resource allocation given New Zealand's ageing population. Rates of both T2DM and high weight status are, however, inconsistently dispersed throughout New Zealand, with different geographic areas having markedly varying outcomes (Berkeley & Lunt, 2006; Ministry of Health, 2016b; Sundborn et al., 2007). This may be influenced by population exposures to the built environment, a term used to describe the physical characteristics of place which are not naturally occurring, as previous research has shown that certain environmental factors can influence chronic health outcomes (Swinburn et al., 2011). This suggests that there are significant opportunities to achieve better health outcomes by considering contextual factors and reducing population exposure to environmental hazards.

Many of these environmental hazards come from exposure to energy-dense products and food environments which are both low in cost and nutrient quality (Creatore et al., 2007). Such environments are often clustered in areas of high deprivation, which may provide some explanation as to why there are significant inequalities in health outcomes in these areas (Ministry of Health, 2016b). In contrast, lifestyle measures that are influenced by the built environment, such as enabling regular physical activity and access to healthy food products, are said to be effective in preventing or delaying the onset of chronic health conditions (IDF, 2015; WHO, 2014). While relationships surrounding high weight status and T2DM are complex and influenced by demographic, behavioural, and environmental characteristics, previous research indicates that local environments may play an important role in chronic disease prevention (Auchincloss et al., 2008; Swinburn et al., 2011). It is therefore vital to investigate the spatial nature of such associations within the New Zealand context in order to better understand patterns relating to both high risk environments and populations.

1.2 Research gap

While research investigating relationships between the built environment and chronic health conditions is abundant, there are still many important research gaps which need addressing. Most notably, further research is needed regarding the spatial understanding of these health issues within New Zealand as much of the existing research into spatial risk factors is theoretical rather than based on evidence from the New Zealand context.

This thesis, in turn, investigates associations between the built environment and health outcomes of T2DM and high weight status. It does so by utilising various measures of the built environment and analysing these in relation to each health outcome separately. In the context of this study, fast food outlets, takeaways, and convenience stores are considered unhealthy exposures and aspects of the built environment which are detrimental to overall health. In contrast, supermarkets, fruit and vegetable stores, physical activity facilities, and greenspace are considered to be healthy exposures and aspects of the built environment which are health-promoting.

Data regarding T2DM comes from the Virtual Diabetes Register (VDR) and considers people of all ages. Data regarding high weight status comes from the Before School Check (B4SC) and considers children aged 4 – 5 years only. The primary reason for this is due to data limitations for weight status in older children and adults, as discussed in Chapter 6. The B4SC, however, is a dataset with national coverage and therefore provides the most detailed and spatially representative understanding of this health issue within New Zealand. The use of these two datasets also provides the opportunity to assess how the built environment may relate to not only outcomes of different chronic health conditions, but also different population groups.

The primary focus of this thesis is on the spatial nature of chronic health issues and the potential associations these may have with determinants of the built environment. As such, the two health outcomes of T2DM and high weight status in children will be analysed and discussed separately and a statistical link between the two will not be considered within this research. Overall, this thesis builds on existing research and addresses current research gaps by focusing on five main areas.

First, in recent years much research has focused on the relationship between the built environment and weight status in adults (Bodor et al., 2010; Boehmer et al., 2007; Boone-Heinonen et al., 2007; Chi, Grigsby-Toussaint, Bradford & Choi, 2013; Oliver et al., 2015; Pearce, Hiscock, Blakely & Witten, 2009; Pearson, Bentham, Day & Kingham, 2014). There has, however, been far less research that considers this relationship with regard to children (Campbell, 2016; Cetateanu & Jones, 2014). Even though recent statistics have shown that high weight status is a significant concern for New Zealand children (Ministry of Health, 2016b; Rajput, Tuohy, Mishra, Smith & Taylor, 2015), spatial research on children's weight status has been lacking within the New Zealand context. Thus, this research aims to address this by providing a detailed understanding of the spatial nature of high weight status in children within urban New Zealand as well as potential associations this health outcome may have with the built environment.

Second, although theory suggests that T2DM is heavily influenced by dietary habits and physical activity (Anjana & Pradeepa, 2017; Bray, 2004), there has been relatively little research into relationships between the built environment and T2DM (Astell-Burt & Feng, 2015; Bodicoat et al., 2014; Christine et al., 2015; Li, Kim & Farley, 2010). This is, again, particularly true within the New Zealand context where few studies have considered the spatial epidemiology of T2DM (Joshy & Simmons, 2006; Sundborn et al., 2007), and none have assessed relationships between this health outcome and the built environment. This thesis aims to address this by investigating not only the spatial epidemiology of T2DM for all urban areas, but also assessing how this health issue is associated with environmental determinants related to diet and physical activity.

Third, research which has been conducted within the New Zealand context has generally used census boundaries for spatial aggregation and analysis (Pearce et al., 2009; Pearson et al., 2014; Sundborn et al., 2007). While this is available at many scales and can aid in understanding spatial associations, such boundaries are primarily administrative and are not designed for spatial analysis. Because of this they are subject to many concerns regarding aggregation (Kwan, 2012). This thesis addresses this concern by using spatial boundaries based on Data Zones. Data Zones are geographic boundaries developed by Zhao and Exeter (2016) which minimise the effects of confidentiality within census data, while adhering to spatial and statistical criteria which ensures they are robust for analysis (Exeter, Zhao, Crengle, Lee and Browne, 2017).

Fourth, research conducted in this field is often limited by the choice of metric regarding spatial accessibility. Previous research has largely relied on the use of census tracts (Dwicksono et al., 2018, Salois, 2012; Zhang et al., 2017), or geographic buffers only (Astell-Burt & Feng, 2015; Carroll et al., 2016; Feng, Astell-Burt, Badland, Mavoa & Giles-Corti, 2018; Pereira et al., 2013). While these are widely used metrics it is also important to assess other measures of spatial accessibility, such as proximity. International studies have sought to achieve this using distance measures (Auchincloss, Roux, Brown, Erdmann & Bertoni, 2008; Choo, Kim & Park, 2017; Drewnowski et al., 2014; Larsen, Cook, Stone & Faulkner, 2015). These are, however, often limited to measuring the distance to the nearest built environment exposure and rarely consider more than one exposure or the effect of distance decay. This thesis seeks to improve upon current environmental measurements of accessibility. It does this by including buffers, both Euclidean and Network based, of varying sizes in order to capture environmental exposures within both walking and driving distances. It also utilises an Enhanced Two-Step Floating Catchment Area (E2SFCA) model which measures distance to the nearest five of each environmental exposure and weights these according to a Gaussian distribution to account for the effect of distance decay.

Fifth, many studies rely solely on the use of frequentist statistical methods. While this is a heavily influential and robust field, it is often ill-suited for spatial research. The main reason for this is because frequentist statistical methods are not generally designed to incorporate the unique nature of spatial relationships. They can also be unreliable when analysing small samples, as is often the case with chronic health outcomes that have been spatially aggregated. Some methods have sought to improve upon this, such as geographically weighted regression (Longley, 2011), and Bayesian modelling (Bayes, 1763; Lee, 2013). This research uses robust spatial and spatio-temporal Bayesian ecological regression models to analyse relationships between both health outcomes, of T2DM and high weight status in children, and environmental exposures. In doing so this thesis seeks to extend current research models which are based solely on frequentist methods to give a deeper understanding of the spatial nature of the data.

Finally, it is important to note that this thesis focuses on urban areas of New Zealand only. There are two key reasons for this: (1) data on health outcomes and environmental exposures are more reliable for urban areas, and (2) environmental exposures, population distributions, and geographic properties in New Zealand are relatively homogeneous within urban areas, as compared to rural areas, and therefore allow more representative comparisons to be made.

In summary, while significant resources are directed toward health research in New Zealand much of this does little to incorporate the inherently spatial nature of place (Mavoa et al., 2019). Thus, current understandings of spatial associations between the built environment and health outcomes of both high weight status in children and T2DM can be improved by: (1) the use of a geographic scale which is based on spatial and statistical criteria, (2) more detailed measures of spatial accessibility to environmental exposures, and (3) an approach to statistical analysis which can account for both spatial and temporal factors. As far as this study is aware there has been no previous research using the spatial scale of Data Zones as well as Bayesian modelling techniques to investigate the spatial epidemiology of the two health outcomes considered, population level T2DM and high weight status in children, and potential relationships with the built environment in New Zealand. This indicates a critical gap in the current literature which this thesis aims to fill. Such research forms a basis on which to better understand spatial associations and potentially formulate policy directed toward environmental influences on chronic health conditions.

1.3 Research approach

1.3.1 Aim and objectives

The aim of this research is to analyse the built environment in urban New Zealand and investigate associations with the spatial epidemiology of two health outcomes: (1) T2DM, and (2) high weight status in children. To achieve the aim of this thesis there were five specific research objectives, to:

1. Review the literature on spatial relationships between the built environment and health, with a focus on T2DM and high weight status in children

2. Create accurate measures of various built environment exposures, based on buffers and distance metrics, for comparison with health outcomes
3. Investigate the spatial distribution of T2DM and high weight status children within urban New Zealand
4. Examine if there is evidence that T2DM and high weight status in children may be influenced by spatial accessibility to various aspects of the built environment
5. Evaluate the overall themes of this thesis and discuss a geospatial understanding of relationships between the built environment and health

Figure 1.1 demonstrates where each research objective is addressed within the thesis.

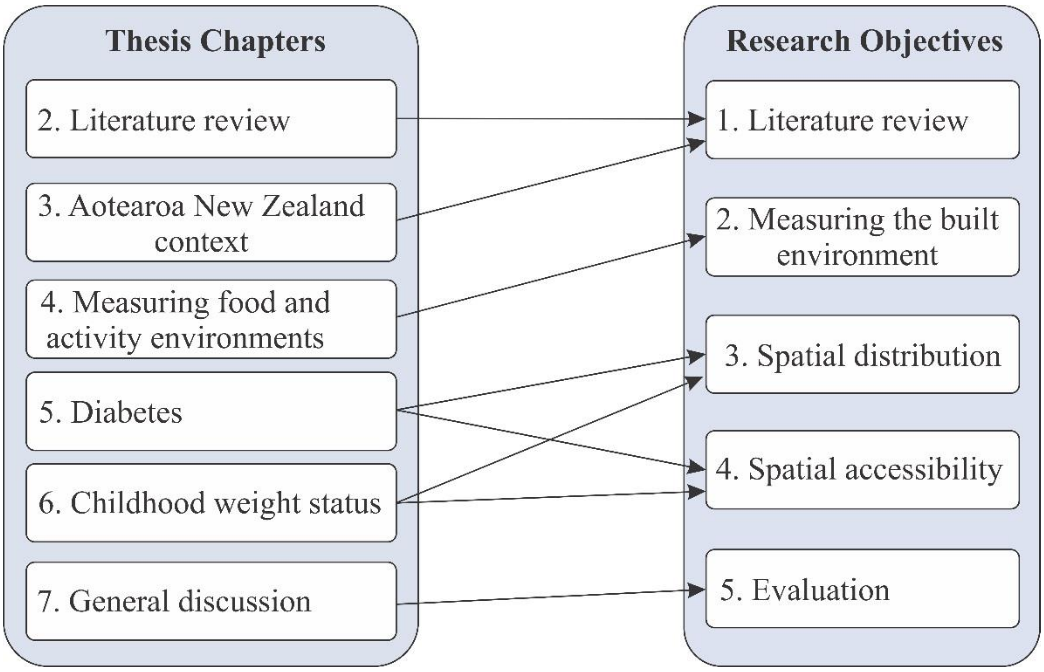


Figure 1.1: *Concordance of research objectives and thesis chapters*

1.3.2 Research approach

This section discusses the overall approach taken within this research. It is intended to be brief, not exhaustive, as the methods are outlined in detail within the relevant thesis chapters and sections. While there are many factors which can affect health outcomes of both T2DM and high weight status in children such as biological, social, and behavioural factors, the focus of this thesis is on geospatial aspects such as contextual factors and environmental influences. Therefore, it is apt that the overall research approach is in fitting with this. There are two main topics within this geospatial theme which will be briefly outlined here: spatial epidemiology and Bayesian modelling.

Spatial epidemiology is defined as the description of spatial patterns regarding disease morbidity and mortality and incorporates methods such as disease mapping, cluster analysis, and ecological analysis (Rezaeian, Dunn, St Leger & Appleby, 2007). These methods are commonly carried out using GIS software, reflecting the spatial nature of the data. Disease mapping is the most basic tool for data visualisation and involves the creation of maps to demonstrate spatial patterning and identify areas of high risk (Rezaeian et al., 2007). These maps typically show the overall rate and standardised rate of the health issue concerned. Additionally, cluster analysis generally involves assessing global and local accumulations of health conditions, with the former investigating the overall pattern and the latter investigating localised areas of risk. This typically involves using both autocorrelation and cluster statistics to understand spatial distributions and dependency such as the 'I' statistic developed by Moran and Getis Ord statistic respectively (Rezaeian et al., 2007). Ecological analysis has been used to assess associations between health outcomes and certain variables of interest (Rezaeian et al., 2007). Within ecological analysis such outcomes and variables are defined by aggregate areas, rather than individuals, and are assessed using a spatial regression model. These methods are utilised within this study in order to gain a deeper understanding of how features of the built environment influence health outcomes of T2DM and high weight status in children.

The second method utilised in this research is Bayesian modelling. Bayesian statistics are based on Bayes theorem (Bayes, 1763). This computes probabilities based on the conditional probability of an event as well as prior information, rather than using fixed values which are based upon frequency (Puga, Krzywinski & Altman, 2015). The resulting probability expresses the degree of belief in an event and is subject to change as new data or information is obtained. Bayesian models are increasingly being used within statistical research which focuses on the spatial nature of data as they are able to accurately model the spatial dependency which is inherent within such datasets while also maintaining an appropriate statistical framework (Lee, 2013).

It is generally considered that there are two empirical Bayesian models which can achieve such results, the simultaneous autoregressive model and the conditional autoregressive model (Lawson & Lee, 2017; Rezaeian et al., 2007). The latter of these models is less complex and is therefore typically preferred. In this study Bayesian modelling for spatial regression was chosen over other statistical methods for two primary reasons: (1) for its accuracy and malleability when dealing with spatially aggregated data, and (2) for its ability to use probabilities over frequencies and thus avoiding issues around small number samples due to aggregation (Lee, 2013). Bayesian modelling is based on probabilities and takes into consideration geographically proximal neighbours, thus it can combine these advantages to produce a robust spatial model. Therefore, this method was chosen over others for its reliable and flexible approach to spatial regression modelling. As with all analyses, however, caution is required when interpreting results.

1.4 Thesis structure

A fundamental focus throughout this thesis is on the utility of spatial and statistical techniques to improve understandings of relationships between the built environment and population health outcomes. This section has provided a short introduction to this field of research, the aims and objectives of this study, as well as the research approach. The remainder of the thesis is structured as follows:

Chapter 2 considers the existing body of literature and begins by giving an overview of the built environment, diabetes, and high weight status. It discusses the definitions of these concepts and theorised relationships. A systematic approach is then taken to identify research which has investigated relationships between the built environment and either T2DM, high weight status, or both, using geospatial or geostatistical methods. The chapter concludes with a review of this research and establishes a research gap in New Zealand which this thesis seeks to address.

Chapter 3 briefly discusses the specificities of the Aotearoa New Zealand context. It is a short chapter which is intended to provide the reader with a discussion of the geographical structure, population composition, social structure, and healthcare system in New Zealand. It gives a partial description of the data used to establish a good contextual understanding for both national and international audiences.

With the contextual understanding established, Chapter 4 is the first of three analytical chapters. It discusses how the built environment was measured and the relationship between environmental exposures and area level socioeconomic status. This chapter provides further information on the data and study categorisation process of the environmental exposures. It also discusses the various measurements of spatial accessibility used and how they were constructed. Results demonstrating relationships between environmental exposures and area level socioeconomic status are then provided before an overall discussion is given.

The following two analytical chapters investigate the spatial epidemiology of health outcomes and potential associations with the built environment. Chapter 5 investigates the relationship between the built environment and T2DM. A short introduction is given before the data and analysis are discussed in detail. The results of individual level characteristics are given first followed by results for spatially aggregated data.

Chapter 6 follows a similar structure to that of the previous chapter but considers the relationship between the built environment and high weight status in children. Again, the chapter begins with a short introduction before a discussion of the data used and analysis techniques. Following the structure of the previous chapter, results of individual level characteristics are given first followed by results for spatially aggregated data.

Chapter 7 provides a general discussion of the overarching themes of this thesis. It begins by discussing the overall themes regarding chronic health conditions in urban New Zealand including demographic patterns, economic accessibility, spatial distributions, and spatial accessibility. It then discusses relevant policy initiatives and notes the limitations of this research. The chapter finishes by providing a brief chapter summary.

Finally, an evaluation of the research objectives is presented in Chapter 8. To conclude, recommendations based on findings from this thesis and areas for future research are presented before providing a concluding statement.

Chapter 2 : The built environment, diabetes, and high weight status: A review of the literature

2.1 Preface

The aim of this chapter is to provide the reader with background knowledge of the topics discussed within this thesis and review the role of geospatial research within the current body of research. In doing so, the limitations of the existing research body are acknowledged which emphasise the need for the current research contribution.

This chapter begins in Section 2.2 by defining and discussing theoretical backgrounds for the three main topics of this study: (1) the built environment, (2) diabetes, and (3) high weight status. It then provides a review of geospatial research in relation to these topics in Section 2.3, and briefly discusses how the review findings informed this thesis, before concluding with a chapter summary in Section 2.4. Therefore, this chapter aims to address Objective 1 (see Chapter 1, Section 1.3.1 on 'aims and objectives'), by comprehensively reviewing the current body of literature on spatial relationships between the built environment and health, with a focus on T2DM and high weight status.

2.2 Overview and theoretical backgrounds

This section is intended to provide an overview of the main topics discussed within this thesis: the built environment, diabetes, and high weight status. Section 2.2.1 focuses on the food and physical activity environments, which are posited to relate to chronic health conditions. Subsequently relevant literature on the two chronic health conditions which are the focus of this thesis, diabetes and high weight status, is discussed (Section 2.2.2). This structure is intended to first provide the reader with an understanding of environmental determinants before outlining the health conditions, and then discussing the relationships between these.

2.2.1 The built environment

The term built environment is used to describe the physical characteristics of place which are not naturally occurring such as retail outlets, land use patterns, community design, road networks, and transportation systems (Li et al., 2010; Morland, Diez Roux & Wing, 2006; Pasala, Rao & Sridhar, 2010; Pearson et al., 2014). This environment is the context in which individual behaviours are set and, as is currently conceptualised within geographical and health literature, can shape individual and collective health by influencing lifestyle patterns. This is particularly notable when considering energy intake and expenditure which are affected by the availability of, and accessibility to, either health-promoting or health-impeding resources. Such relationships are, however, multi-directional.

Energy intake through the food environment and energy expenditure through the physical activity environment are both important aspects in addressing and understanding the energy balance equation and subsequent population health outcomes. Environments which simultaneously encourage the consumption of food, particularly that which is nutrient-low and energy-dense, and discourage physical activity are often termed obesogenic environments and can contribute to changes in energy balance (Hill & Peters, 1998; Reidpath, Burns, Garrard, Mahoney & Townsend, 2002; Swinburn et al., 2011). Obesogenic environments are largely associated with urban areas where there is increased exposure to health risks due to higher numbers and range of food opportunities and decreased physical activity which are often reflective of zoning initiatives, community design, and population density (Cities Changing Diabetes [CCD], 2015).

Previous research has suggested that changes in behaviour such as healthy eating and regular physical activity are often unsustainable when living in environments which are unsupportive (Auchincloss et al., 2009; Christine et al., 2015). This can include either increasing accessibility to resources which have negative influences on health or decreasing accessibility to resources which have positive influences on health. It is important to note, however, that the availability and accessibility of resources does not necessarily correspond to their utilisation which may also be influenced by quality, acceptability, and affordability. There may also be certain populations which are more heavily influenced by their immediate environments due to mobility limitations or financial constraints (Ministry of Health & New Zealand Public Health Advisory Committee, 2010). This can include older people and children, people with limited financial resources or little access to transport options, and people living with disabilities. While rising health concerns are a somewhat normal response to such environments it has been argued by Swinburn et al. (2011) that such environments have also arisen as a normal responses to the economic and political environments in which both governments and businesses find themselves in.

2.2.1.1 The food environment

The food environment has been defined as the opportunities and conditions which influence population food choices including accessibility, location, type, and number of food sources within a community as well as food advertising and marketing (Haynes-Maslow & Leone, 2017; Li et al., 2010; Townshend & Lake, 2009; Vandevijvere, Chow, Hall, Umali, & Swinburn, 2015a). Access to quality fresh food has been shown to promote healthy food choices and eating behaviours (Auchincloss et al., 2008). Swinburn et al. (2013) have, however, argued that processed, energy-dense, and nutrient-poor food products dominate food environments in the modern age and heavily contribute to social norms around eating behaviours. Many foods are believed to have a negative influence on health, notably those which are energy-dense and high in saturated fats such as fast food and pre-packaged convenience foods (Creatore et al., 2007; Fraser, Edwards, Cade & Clarke, 2010; Morland et al., 2006). These food products are increasingly accessible in urban environments and act as an influential supply-side driver in the over-consumption of unhealthy foods. Such products are relatively inexpensive and their influence is compounded by heavy marketing and promotion.

Research suggests that access to food products is not uniformly distributed throughout communities and residential environments (Astell-Burt & Feng, 2015; Auchincloss et al., 2008). Those with higher incomes may have access to more opportunities for food purchasing and therefore may be able to achieve a healthier lifestyle more easily (Creatore et al., 2007). In fitting with this theory, research has shown a disproportionate number of unhealthy food outlets in socioeconomically deprived areas and areas with high ethnic minority populations (Bodicoat et al., 2014; Fraser et al., 2010). Research on such ‘food deserts’ has been conducted predominately within the United States (Walker, Keane & Burke, 2010), with research from other contexts demonstrating that this is not restricted to unhealthy outlets only and that highly deprived areas have more access to all types of food outlets (Pearce, Day & Witten, 2008a). Explanations behind this social patterning are likely reflective of many facets such as land values and zoning.

Lowe et al. (2009) have also argued that the effect of negative food environments may extend beyond weight gain and physical health alone as food abundant environments may also affect food-related cognition. It has been suggested that to protect against energy deficits, even when a caloric deficit is not present, the body will respond to a wide range of highly palatable foods with a need to consume them due to appetite motives (Lowe et al., 2009). The ingestion of palatable foods will also trigger a dopamine release in the body which, through conditioning, may begin to respond to environmental cues of availability and exposure through psychological processes (Lowe et al., 2009). Hill and Peters (1998), in turn, have argued that the body's defences against the accumulation of excessive energy storage are weak when food is readily available and abundant, as it is in an obesogenic environment.

2.2.1.2 The physical activity environment

The built environment also plays an important role in facilitating physical activity through the physical activity environment. Access to opportunities for physical activity and exercise within the built environment include greenspace, parks, open spaces and courts, walkability, community centres, pools, infrastructure for active transport, and recreational facilities such as gyms (Brown et al., 2004; Creatore et al., 2007; Gebreab et al., 2017; Lachowycz & Jones, 2011; Lee, Rushworth & Napier, 2017; Li et al., 2010; Townshend & Lake, 2009). Such places provide opportunities for people to exercise outdoors and indoors but their use can be dependent on economic resources, safety concerns, and aesthetic qualities as well as proximity and density. Population reductions in physical activity levels have been influenced by urban sprawl and developments such as mechanisation, industrialisation, and computerisation which are aimed at saving labour and reducing physical exertion in the everyday activities of modern lifestyles, encouraging an increase in sedentary behaviours (Egger & Swinburn, 1997; Sallis, Floyd, Rodriguez & Saelens, 2012). Engaging in regular physical activity has, however, been shown to reduce the risk of chronic health conditions and non-communicable diseases through biological mechanisms such as reductions in adipose tissue, particularly abdominal adiposity, triglyceride levels, blood pressure, and stress levels (Anjana & Pradeepa, 2017; WHO, 2002).

2.2.2 Diabetes and high weight status

2.2.2.1 Diabetes: An overview

In 1921, Canadian scientists Frederick Banting and Charles Best isolated a substance from the pancreas which they termed 'isletin', now known as insulin (IDF, 2015). Insulin is vital in both the storage and controlled release of chemical energy derived from food products and allows glucose to enter the cells of the body where it is subsequently converted to energy. Failure to control blood glucose levels is a product of insulin resistance and dysfunction of the body cells which release insulin, the pancreatic islet β-cells (Kahn et al., 2006). A biological feedback loop exists in healthy persons whereby β-cells increase the supply of insulin in response to the demand from muscle, the liver, and adipose tissue (Kahn et al., 2006). Therefore, insulin levels must be proportionate to changes in insulin sensitivity. Failure within this feedback system, and thus a deviation from normal glucose tolerance, underpins the biological development of diabetes as the body's need for insulin is stronger than the pancreas' ability to produce it. This can be a result of either body cells becoming resistant to the actions of insulin or not producing enough insulin naturally (Cox, Boyle, Davey, Feng & Morris, 2007; Scobie & Samaras, 2014). The former of these renders insulin ineffective and results in Type 2 Diabetes Mellitus (T2DM), while the latter characterises Type 1 Diabetes Mellitus (T1DM). T2DM is widely considered to be the most prevalent form of diabetes, with over 90% of adults affected having this variation of the disease (IDF, 2015; Ministry of Health, 2015). T2DM, once termed 'adult onset diabetes' and considered a health condition of older populations, is now the most frequently encountered metabolic disorder worldwide and is increasingly a cause of morbidity and mortality in middle-aged and youth populations (Anjana & Pradeepa, 2017; Chatterjee, Khunti & Davies, 2017; WHO, 2015a).

High blood glucose levels can put people at risk of further pathophysiological changes and complications such as cardiovascular disease, blindness, renal disease, kidney and other organ failure (Beagley, Guariguata, Weil & Motala, 2014, IDF, 2015). Impaired glucose tolerance (IGT), also termed pre-diabetes, characterised by raised blood glucose is also a significant health concern, but one which has not yet reached the critical level required to be given a diagnosis of diabetes (IDF, 2015). Individuals with both IGT and established diabetes are estimated to have between a 1.5 and 3-fold higher risk of mortality when compared to those with healthy glycaemic levels (Beagley et al., 2014). Importantly, however, IGT will not always develop into diabetes with evidence supporting the effect of lifestyle interventions in preventing progression (IDF, 2015; Wright, Wilson, Smith, Duncan & McHugh, 2017).

The criteria for the measurement of diabetes in New Zealand has been mmol/mol since 2012, with cut-offs of HbA1c ≥ 50mmol/mol for diabetes and HbA1c 41-49 mmol/mol for IGT (Coppell et al., 2013). Refer to glossary for more information on HbA1c. Ahlqvist et al. (2018) have argued that the current classification of diabetes is problematic, however, as it can be highly heterogeneous within groups and have called for a refined classification based on sub-groups of differing risk and disease progression. This presents a progression in the biological understanding of diabetes and may help tailor early treatment interventions and further understand potential relationships with environmental factors.

2.2.2.2 High weight status: An overview

High body weight can have adverse effects on health and is thought to be a risk factor for many preventable health issues including T2DM, heart disease, hypertension, stroke, and certain cancers (Reidpath et al., 2002; WHO, 2014). Maintaining an appropriate body weight and adipose level is heavily influenced by energy balance which accounts for energy intake through food and nutrients and energy expenditure through biological functions and physical activity. This energy balance varies among individuals due to differences in lipostatic set point and metabolic rate, which can in turn influence ones activity preferences and appetite control (Campbell, 2016). An increase in energy intake, without subsequent increases in energy expenditure, will ultimately result in weight gain until the point where resting metabolic rate and increased energy, which is required to move a larger body size, have again balanced (Vandevijvere et al., 2015a). High body weight status is defined by a ratio of body weight to height squared (Biing-Hwan, 2005), and is commonly classified into categories of overweight and obese which are characterised by high amounts of adipose tissue, or body fat, in relation to body mass. Overweight and obesity are typically measured by Body Mass Index (BMI), with classifications of BMI $\geq$25 kg/m^2 and $\geq$30 kg/m^2 respectively (WHO, 2014). Furthermore, a morbidly obese classification is that of BMI $\geq$40 kg/m^2 (Ministry of Health, 2016b). This commonly used classification system can be problematic, however, with research suggesting ethnic-specific classifications or a system based on waist circumference measurement may be more accurate (Seidell, 2000).

2.2.2.3 Diabetes and high weight status: The extent of the problem

Worldwide, diabetes prevalence was estimated at 285 million people in 2010, a number which is projected to increase to over 400 million by 2030 when diabetes is expected to be among the top 10 leading causes of mortality (Egede & Ellis, 2010; WHO & IDF, 2004). In 2015, approximately 5 million people died from diabetes, this is equivalent to one death every six seconds and approximately 6% of the total world mortality (IDF, 2015; Scobie & Samaras, 2014). Furthermore, the World Health Organization (WHO, 2014) estimates that 30-80% of diabetes cases are either asymptomatic or undiagnosed which can prolong damage to the body and result in serious health consequences even before diagnosis, contributing to the health burden.

Within New Zealand, diabetes was first measured in 1967 (Murray et al., 1969) and rates have increased over time, consistent with worldwide trends. This increasing prevalence is reflective of many factors such as better detection, slower disease progression, demographic changes, and rising incidence. According to the Ministry of Health (2015) more than 250,000 New Zealanders, approximately 6% of the total population, live with diabetes and T2DM in particular is posing serious challenges to the healthcare system. Furthermore, in 2014 the number of people who were diagnosed with diabetes is reported to grow by close to 40 people every day (Ministry of Health, 2015). The highest prevalence within New Zealand is typically seen in people of Indian, Pacific, and Māori ethnicities as well as those living in socioeconomically deprived areas and those with long-term mental illnesses (Ministry of Health, 2015). Diabetes also disproportionately affects older adults, with at least one in six of those aged 65 and over diagnosed with diabetes in 2015 (Ministry of Health, 2015). There is also a high prevalence of IGT in New Zealand, estimated at 18.6% (Coppell et al., 2013). This is over double that of worldwide estimates of IGT (Ogurtsova et al., 2017), and suggests that diagnosed diabetes will continue to increase.

Additionally, obesity prevalence has doubled worldwide since 1980 and it has been estimated that approximately 40% of adults, aged 18 years and over, have high body weight (WHO, 2014). Furthermore, more than 40 million children, aged less than 5 years, are also classified as having high body weight (WHO, 2014). This affects not only mortality, but also the quality of life of those affected. An estimated 3.4 million deaths and 93.6 million Disability Adjusted Life Years (DALYs) were attributable to high body weight in 2010 (WHO, 2014). As a unit of health loss, the loss of one year, lived in full health, represents one DALY.

High body weight is also a significant health concern in New Zealand with three out of ten adults, and one out of nine children, classified as obese (Ministry of Health, 2016b), among the highest rates worldwide. The percentage of people classified as morbidly obese is also continuing to grow within New Zealand, estimated at 5.1% in 2016 which is a substantial increase from 3.4% in 2007 (Ministry of Health, 2016b). Additionally, high body weight is thought to account for over 9% of all health lost in New Zealand, making it one of the most prominent preventable health risks (Ministry of Health, 2016a). Ethnic minorities such as Māori and Pacific Peoples and those living in socioeconomically deprived areas are shown to have the highest prevalence (Ministry of Health, 2016b). Alarmingly, 66% of adults and 30% of children of Pacific ethnicity are obese, while 47% of adults and 15% of children of Māori ethnicity are also obese (Ministry of Health, 2016b). This means that Māori children are 1.6 times as likely, and Māori adults are 1.7 times as likely, to be obese compared to non-Māori. Additionally, children of Pacific ethnicity are 4 times as likely, and adults of Pacific ethnicity

2.4 times as likely, to be obese compared to those on non-Pacific ethnicity. Furthermore, children living in the most deprived areas are shown to be five times as likely to be obese when compared to children in the least deprived areas (Ministry of Health, 2016b). This association, while also present for adults, showed a far stronger gradient for children. It has been argued by Kelly and Swinburn (2015) that 80% of obese children will remain obese during adulthood, suggesting that the prevalence of high body weight in deprived areas may be further exacerbated in the future.

2.2.2.4 Diabetes and high weight status: The risk factors

T2DM and high body weight have increased alongside societal, demographic, and cultural changes. There are various biological, behavioural, and environmental risk factors for their development although there is still much to be learned about both direct and indirect causes.

Regarding individual factors, both T2DM and high body weight are commonly thought to be a consequence of physical inactivity, sedentary behaviours, high caloric intake or poor dietary behaviours, age, ethnicity, and genetic predisposition (Agardh et al., 2011; Al-Rubeaan, 2010; Cox et al., 2007; IDF, 2015; Laraia et al., 2012; Scobie & Samaras, 2014; WHO, 2015a). Biologically, the gene variant P12A polymorphism is thought to be associated with insulin sensitivity and the most frequently cited genetic mutations related to high body weight are that of the melanocortin-4 receptor, accounting for approximately 4% of severe obesity cases, and leptin production (Egger & Swinburn, 1997; Kahn et al., 2006). Additionally, approximately 58% of diabetes worldwide attributable to high body weight (WHO & IDF, 2004), although this can also be influenced by the distribution of body fat which can also apply to leaner individuals (Kahn et al., 2006). This relationship functions through biological pathways as adipose tissue which is characteristic of obesity releases non-esterified fatty acids, pro-inflammatory cytokines, and glycerol. These are thought to be related to insulin resistance by interfering with insulin signalling through lipotoxicity (Kahn et al., 2006; Scobie & Samaras, 2014). Research has also suggested that mental health issues may contribute to glucose and weight control, including depression (Egede & Ellis, 2010) and stress (Brown et al., 2004).

Furthermore, indigenous peoples are often disproportionately affected by diabetes, however this varies substantially. For example, New Zealand Māori and North American Sioux have a far greater prevalence than their national populations, however, Chilean Aymara and Malaysian Orang Asli have a much lower prevalence than their national populations (IDF, 2015; Scobie & Samaras, 2014). This is thought to be attributed to the fact that the latter still follow a very traditional lifestyle while the former have undergone relatively rapid acculturation, a term used to describe the cultural, social, and psychological changes which can arise from the amalgamation of cultures. Research has also argued that there is evidence that metabolic disorders and body weight may be influenced in-utero and during the early post-natal period, critical times for both endocrine and metabolic plasticity, by poor nutrition which may alter metabolic processes by adapting body tissues to favour the storage of nutrients (Arenz, Rückerl, Koletzko & von Kries, 2004; Campbell, 2016; Gillman et al., 2001; Kahn et al., 2006). Such mechanisms may in turn signal a deleterious genetic interaction and predispose an individual to the development of health conditions such as obesity and T2DM.

While biological and genetic factors are undoubtedly important risk factors for T2DM and body weight research has demonstrated that individual characteristics are shaped by the physical, social, and cultural environments in which one lives (Berkeley & Lunt, 2006; CCD, 2015; Dendup, Feng, Clingan & Astell-Burt, 2018; Jack, Liburd, Vinicor, Brody & Murry, 1999). Local environments, acting as proximal determinants of individualistic behaviours, are thought to be able to either facilitate or constrain individual choices around both dietary intake and physical activity patterns (Morland et al., 2006; Swinburn et al., 2011). Egger and Swinburn (1997) have, in turn, argued that the increase in body weight and subsequent health issues such as T2DM should be regarded as a normal response to an abnormal environment. Such environments not only impact on people's susceptibility to poor health outcomes, but can also influence their ability to effectively manage it.

The hypothesis that T2DM originates from an interplay between both genetic and lifestyle factors, that latter of which are heavily influenced by the surrounding environment, was first suggested over 50 years ago (Neel, 1962). Additionally, George Bray has expressed the relationship between genetics, environments, and obesity as "the genetic background loads the gun, but the environment pulls the trigger" (Bray, 2004, p115). Yet, the individualisation of risk has taken responsibility away from population drivers and causes of health outcomes which are environmentally and socially determined. Potential epigenetic effects, meaning those which arise from non-genetic influences on gene expression, such as behavioural and environmental factors have, however, begun to receive increased attention (Campbell et al., 2016; CCD, 2015; Egger & Swinburn, 1997; Swinburn et al., 2011). Thus, in order to understand the determinants of diabetes and high body weight individualistic susceptibility and behaviours, as well as the wider ecological context in which such behaviours are constructed, must be considered.

Environmental factors which drive demographic and epidemiological changes include distal systematic drivers such as the globalisation of economic processes, urbanisation, changes in agricultural and trade policies, dietary transitions, demographic changes, increases in sedentary behaviours, and reductions in physical activity due to increasing mechanisation (Al-Rubeaan, 2010; Basu, Yoffe, Hills & Lustig, 2013; Goran, Ulijaszek & Ventura, 2013; IDF, 2015; Scobie & Samaras, 2014; WHO, 2002). Population factors such as health education, social support, values, and cultural or societal norms may also significantly influence health behaviours and outcomes. Such factors represent a complex system where dependencies, interactions and relationships give rise to larger collective behaviours.

The industrial revolution marked a transitional point, changing how food products were produced, processed, and subsequently consumed. Compounded by increasing urbanisation, economic development, innovations in technology, and changing marketing techniques this has led to significant changes in the landscape of the food environment and composition of modern diets (WHO, 2002; Swinburn et al., 2011; Vandevijvere et al., 2015a). The importation of cheap food items that are highly processed, energy-dense, and nutrient-poor has become increasingly convenient and popularised, leading to changes in both food purchasing behaviours and consumption patterns. This is further compounded by the high palatability of such foods. The 1960s and 1970s also saw a transitional point, whereby an increasing food energy supply led to higher energy intake and subsequently an increase in population weight and associated health issues (Swinburn et al., 2011). It has been suggested that there are two distinct phases within this transition, the ‘move-less-stay-lean’ phase characterised by a decrease in both energy intake and physical activity throughout the period 1910-1960, and the ‘eat-more-gain-weight’ phase characterised by an uptake in energy intake and subsequent rise in population weight status from the 1960s onward (Swinburn et al., 2011). An environment full of choice also brings with it an element of complexity, making decisions potentially subconscious or automatic, a response termed passive over-consumption (Swinburn et al., 2011). Furthermore, given the demand of modern lifestyles people may also find that they have less time for food preparation, leading to increases in food eaten outside of the home and lesser knowledge about the quality and composition of the food products being consumed.

Researchers have argued that the marketing and replacement of fat with processed sugar and starches by the food industry have contributed to population increases in total energy intake which in turn is driving increases in T2DM and obesity among other health issues (Goran et al., 2013; Mann, Swinburn, Beaglehole, Mhurchu & Jackson, 2015). Poor β-cell function, as discussed previously, is thought to be related to the intake of dietary sugars in particular as high consumption of sugars can require continued insulin secretion and over time lead to dysfunction of the β-cells, and subsequently the development of T2DM (Goran et al., 2013). According to research by Basu et al. (2013) countries worldwide have experienced a rise in the average sugar supply, going from 218 kilocalories per person every day in the 1960s to an excess of 280 kilocalories per person every day in modern times, with the majority of this increase taking place in the last decade. Basu et al. (2013) have also established that countries which made a conscious effort to lower sugar availability saw a reduction in diabetes prevalence, even after controlling for other variables, and that longer exposure to high sugar availability was associated with accentuated prevalence of diabetes. Additionally, when there are threats within the surrounding environment the body is thought to respond according to the ‘fight or flight’ response by activating the adrenal medulla and releasing hormones such as epinephrine and norepinephrine into the blood stream (Adamo, 2014). If such bodily reactions are frequently simulated, which can be produced by living in a threatening environment, the recovery time needed to reach a normally regulated level may be impaired (Stafford et al., 2007). Such physiological responses, if repeated, may produce strain on the body termed allostatic load which is thought to be a contributor to high body weight (Stafford et al., 2007). In this sense, Kahn et al. (2006) have argued that health outcomes such as obesity and T2DM are worldwide issues neither of infection nor famine, but of surplus.

Mechanisms by which body weight increases and T2DM develops may vary substantially between differing levels of social strata and are by no means uniformly distributed. An increase in energy-dense foods has led to diets based on refined sugars and added fats becoming more affordable than recommended diets typically based on vegetables, fruit, and lean meats (Drewnowski, 2004). Changes toward increased portion sizes of highly processed foods are compounded by relatively higher costs of nutritious food, whether this is perceived or real cost (Creatore et al., 2007). Thus, due to financial constraints and attempts to reduce dietary costs people may find themselves with increased energy intakes, a significant risk factor for high body weight and associated health issues such as T2DM. Drewnowski (2004) has argued that the ability to adopt a healthier diet may not be attributable to psychosocial factors and is more heavily influenced by the socioeconomic position of the household and the cost and range of products in the surrounding food environment. Many studies have also found a relationship between T2DM and socioeconomic status (Agardh et al., 2011; Connolly, Unwin, Sherriff, Bilous & Kelly, 2000; Kim et al., 2015; Mezuk et al., 2016). Connolly et al. (2000) have noted, however, that such relationships are not evident when considering T1DM. Causal pathways by which such relationships may occur are complex but may include both environmental and lifestyle factors such as limited access to healthcare services, a paucity of health-promoting resources, poorer quality of care, higher crime rates and physical incivilities, social norms, and health behaviours (Agardh et al., 2011; Brown et al., 2004; Laraia et al., 2012; Mezuk et al., 2016). Furthermore, Brown et al. (2004) have argued that the accumulation of negative exposures is perhaps more important than any singular dimension alone, reinforcing why multiple environmental variables as well as socioeconomic deprivation were used within this study.

2.2.2.5 Diabetes and high weight status: The healthcare costs

Finally, there are significant healthcare costs of morbidity and mortality related to both diabetes and high body weight, thus it poses not only a challenge to individuals and families but also the healthcare system. Direct healthcare costs include factors like medication, hospitalisation, and continuing care while indirect costs can include factors like loss of productivity and premature death (Ministry of Health, 2015). T2DM, as a chronic disease which develops gradually, requires both medical care and self-management including adhering to a healthy diet, adequate physical activity, health education, and in many cases prescription of pharmaceutical medications (Knowler et al., 2002; Langenberg et al., 2014). Globally, using International Dollars (ID), the IDF (2015) estimate that between ID795-1404 billion of global health spending was spent on diabetes in 2015. Additionally, in New Zealand, government funded healthcare costs for diabetes were estimated at NZD540 million in 2006/07, 3% of the national health expenditure (Kedgley & NZPHC, 2007). It is also estimated that this could increase to 15% by 2021 if sufficient action is not taken (Kedgley & NZPHC, 2007). Healthcare costs attributable to high body weight in New Zealand are also substantial, estimated at NZD624 million in 2006, 4.4% of the national healthcare expenditure (Lal, Moodie, Ashton, Siahpush & Swinburn, 2012). Expenditure related to both diabetes and high body weight continue to be driven by population growth, urbanisation, and societal changes and pose an ongoing concern, with the Ministry of Health (2016a) noting that expenditure is not necessarily reduced by improvements in population health outcomes.

2.2.3 Section summary

To conclude, while the globalisation of economic processes, mechanisation, and developments in technology have signified economic and commercial successes they have also had the unfortunate consequence of being implicated in the causal pathway for rising epidemics of preventable chronic health conditions, such as high body weight and T2DM, through changing food and physical activity environments. This will likely continue unless environments are created which minimise population energy intakes and enable access to quality food products and physical activity spaces which are health-promoting.

2.3 The contribution of geospatial research: A review

This section provides a review of the literature, with a focus on research which has used geospatial methods to investigate potential associations between the built environment and health outcomes of both T2DM and weight status. A review was conducted to assess the scope of geospatial methods used and identify relevant environmental variables which will, in turn, help to shape the metrics used in this thesis.

This section will first go over the methodological approach used within the review. It will then present the results of the review, before concluding with a discussion and section summary.

2.3.1 Methodology of literature review

2.3.1.1 Search strategy

A systematic search of international and national peer-reviewed articles addressing associations between the built environment and health outcomes of T2DM and/or high weight status was conducted in June 2018 using the following electronic databases: Web of Science, Science Direct, Scopus and PubMed. This reviews roughly the past two decades of research in order to capture the most recent work and significant developments over time. Search terms were based on keywords addressing the built environment, diabetes, and obesity (Appendix A). The title and abstract of each article were analysed and a full-text analysis was undertaken for articles deemed relevant. Reference lists from articles were also used to search for publications which may not have been identified in initial database searches.

2.3.1.2 Selection criteria

Studies relating a built environment exposure to either T2DM, high weight status, or both were considered if published between January 2000 and June 2018, in the English language, and were from a peer-reviewed sources (internationally and nationally). Articles were included if T2DM or obesity/weight status were one of the main health outcomes and macro-level environmental correlates (e.g. aspects of the environment which are affected by large scale processes and often measured at an aggregated level) were included. A full description of the search strategy is provided in Figure 2.1. Studies were excluded if they:

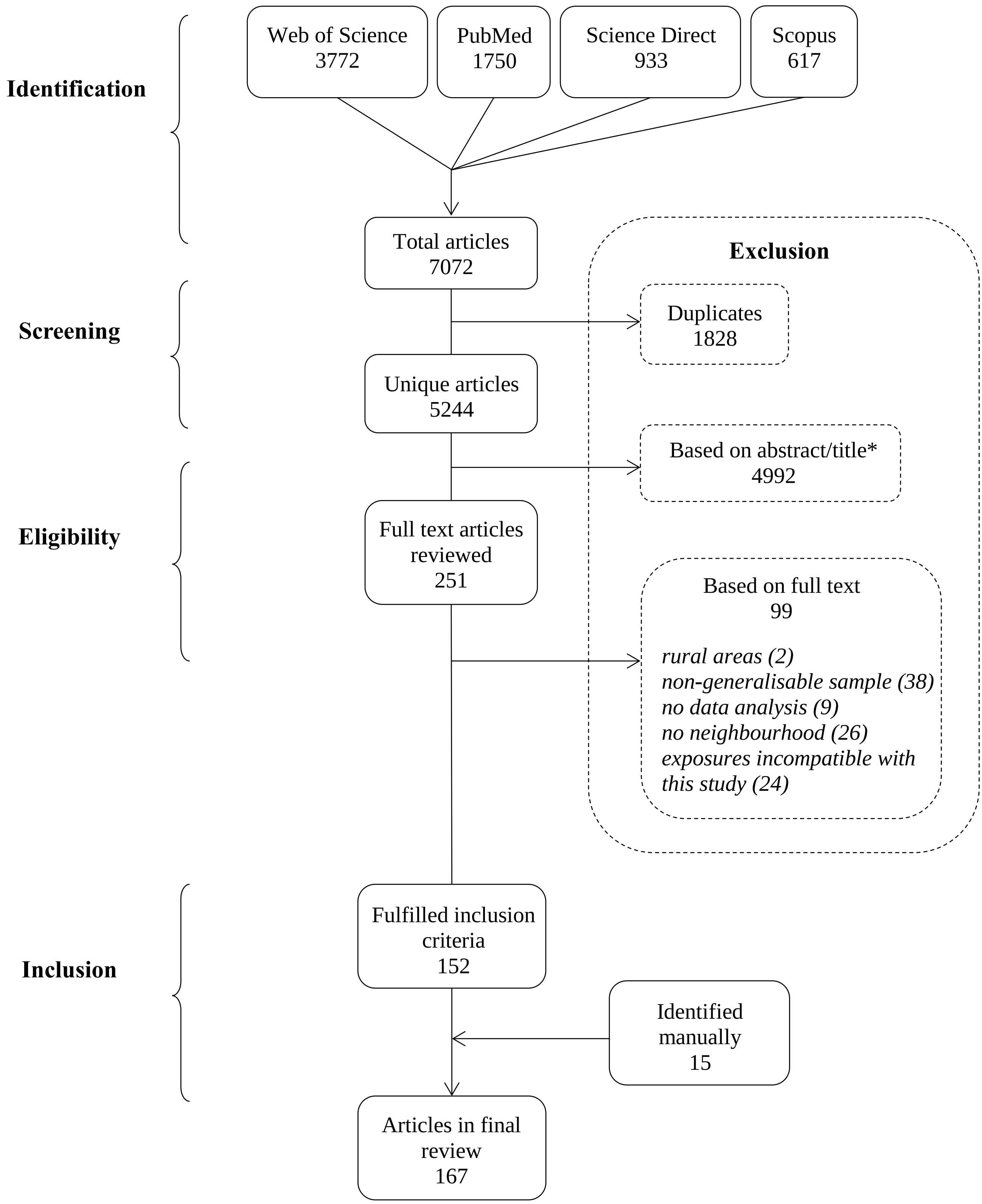
- focused on rural areas only
- focused on Type 1 Diabetes Mellitus (T1DM) only
- were reviews or editorials
- only assessed environmental exposures as potential confounders
- focused primarily on socioeconomic characteristics with no environmental measure
- had a specific study population, meaning that results are non-generalisable

2.3.1.3 Extraction and classification

The following information was extracted:

- country of data collection
- study design (cross-sectional or longitudinal)
- key environmental exposures, as related to this study
- objective and perceived measures of the built environment
- measured or self-reported health outcomes
- the direction of reported associations
- geographic scale/measure used

Built environment exposures were categorised into: 1) the physical activity environment, referring to opportunities for engagement in physical activity, and 2) the food environment, referring to opportunities to purchase food products. Additionally, the definition of geographic scale/measure considers studies which used administrative units (such as census tracts), buffers (both Euclidean and Network-based), and a non-standard definition of neighbourhood (such as natural boundaries).



* *Including those which were not original research (e.g. reviews, editorials)*

Figure 2.1: *Flowchart of search process and number of articles for inclusion in final review*

2.3.2 Result of literature review

After duplicates were removed, 5,244 articles were screened for inclusion based on title and abstract. Of these 4,992 articles were excluded based on title and abstract. A further 99 articles were excluded based on full-text reviews for the following reasons; focused on rural areas, had a non-generalisable sample, had no primary data analysis, had no definition of neighbourhood, or had environmental exposures which were not in fitting with this study (Appendix A). Non-generalisable sample refers to studies that focused on one specific population group only (e.g. one gender group aged over 65 years, veterans only, or women of childbearing age). Studies focusing on certain age groups for children were included, but studies focusing on one age segment of the adult population (e.g. 65+) were not. This is due to the smaller amount of studies that focused on children overall and the vast differences of the adult-specific age group studies. Studies with children focusing only on one gender and ethnic/income group were also classed as non-generalisable. Thus, 152 articles fulfilled the final inclusion criteria and a further 15 articles were identified manually for inclusion in the final review (Appendix A). Table 2.1 presents summarised results, stratified by country and count, on associations between the built environment and health outcomes of T2DM and weight status. Full details of all studies are given in Appendix A.

Table 2.1: *Characteristics of included studies by country and count*

		US[1]/ Canada	**Central/ South America**	**Australia/ NZ[2]**	**Asia/ Africa**	**United Kingdom**	**Europe[3]**
Design	Cross-sectional	89	5	11	4	20	8
	Longitudinal	17	0	4	2	3	3
	Both	0	0	1	0	0	0
Health Condition	T2DM	13	0	3	0	3	1
	Weight status	87	4	12	6	20	10
	Both	6	1	1	0	0	0
Outcome Measure	Self-reported	55	3	8	1	7	5
	Measured	50	2	7	5	15	6
	Both	1	0	1	0	1	0
Domain	Food	54	1	7	4	10	2
	Physical Activity	15	1	4	1	9	3
	Both	37	3	5	1	4	6

Table 2.1: Characteristics of included studies by country and count … continued

Exposure Measure	Objective	91	2	14	5	23	8
	Perceived	6	1	0	0	0	2
	Both	9	2	2	1	0	1
Association	Expected	52	0	6	2	12	6
	Null	17	2	4	2	3	2
	Mixed/Unexpected	37	3	6	2	8	3
Geographic Measure	Census tract	59	4	5	1	8	6
	Buffers	26	1	7	1	9	2
	Proximity	4	0	0	0	1	1
	Various	17	0	4	4	5	2

[1]United States; [2]New Zealand; [3]Excluding the United Kingdom

Articles included in the final review ranged from 2003 – 2018, with 91.6% (*N=153*) published in the last decade. In total, 82.0% (*N=137*) of studies used a cross-sectional design, 17.4% (*N=29*) used a longitudinal design, and 0.6% (*N=1*) used both. The majority of the reviewed studies, 63.5% (*N=106*) of articles were from North America, with a further 13.8% (*N=23*) from the United Kingdom (UK), 9.6% (*N=16*) from Australia and New Zealand, 6.6% (*N=11*) from other European countries, 3.6% (*N=6*) from Asia and Africa, and 2.9% (*N=5*) from Central and South America (Table 2.1).

Regarding health outcomes, 83.2% (*N=139*) of articles considered obesity, 12.0% (*N=20*) considered T2DM, and 4.8% (*N=8*) considered both. Studies focusing on children constituted only 29.3% (*N*=49) of all studies, all of which considered weight status as the health outcome. Regarding the built environment, 85.6% (*N=143*) of studies used objective measures of the built environment which were generally derived using GIS, 5.4% (*N=9*) of studies used perceived measures, and 9.0% (*N=15*) of studies used a combination of both. Furthermore, 46.7% (*N=78*) of studies considered the food environment alone, 19.8% (*N=33*) considered the physical activity environment alone, and 33.5% (*N=56*) considered a combination of both. The correlates/sub-domain column (Appendix A) indicates heterogeneity across studies in the definition and use of 'built environment'. Due to the diversity and range of exposure definitions and statistical methods used, these are not reported in detail here. Additionally, studies used various measures pertaining to social and objective behaviours. These were not included as covariates in the resulting table as they are not in fitting with the environmental exposures discussed in this study, and therefore are not the focus. They are however important areas of research which warrant a review of their own.

There was also heterogeneity in the geographic scale and/or measure used. Details from the 'geographic measure' column (Table 2.1) can be in reference to aggregated areas, buffers, and distance measures. Aggregated level data was most commonly used, although this was often accompanied by individual-level data in the form of a hierarchal/multilevel model structure. Buffers, both Euclidean and Network-based, and distance measures were also extensively used, ranging from 0.25 – 5 miles and 0.4 – 3.2 km. Overall, the majority of studies (59.3%, *N=99*) used aggregated data based on administrative boundaries, classified as 'census tract' (Table 2.1). A substantial number (37.7%, *N=63*) used buffers, of both Euclidean and network variations, and measures of distance. Finally, only a small number (3.0%, *N=5*) used a unique definition of neighbourhood such as natural boundaries.

Findings from the reviewed articles were classified as 'expected', 'null', or 'mixed/unexpected'. Expected results are in line with the studies hypotheses, null results signify studies which did not reach statistically significant conclusions, and mixed/unexpected include studies which had unexpected or mixed results for different environmental exposures or spatial scales. Of the 167 included studies, 46.7% (*N=78*) demonstrated results that were broadly consistent with the hypotheses of the study, whereas 18.0% (*N=30*) of studies reported that they did not find statistically significant results, and 35.3% (*N=59*) reported mixed and/or unexpected results (e.g. not in the hypothesised direction). Figure 2.2 below demonstrates these results in more detail.

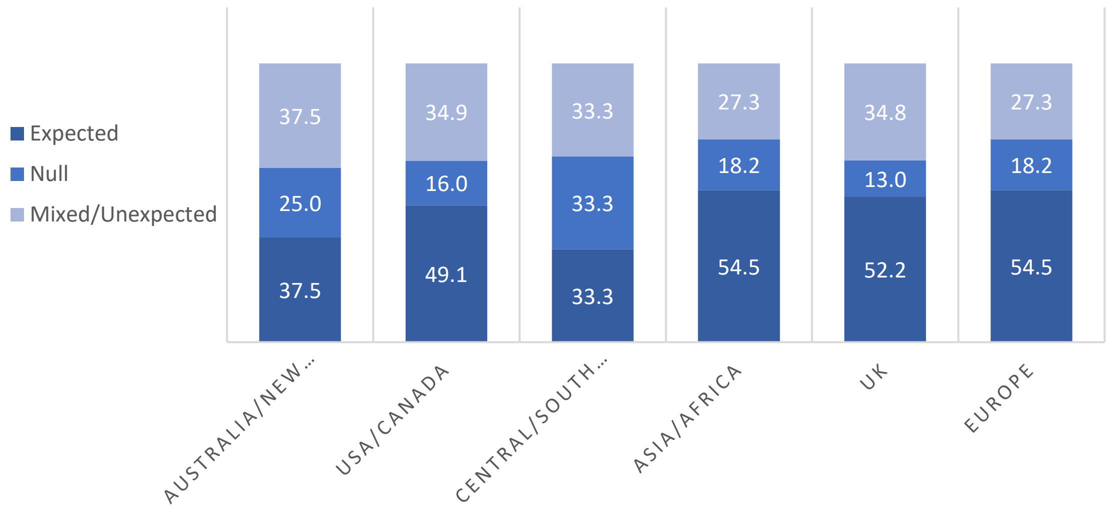


Figure 2.2: *Reported findings from reviewed articles*

Roughly half of all studies from USA/Canada, Asia/Africa, and UK/Europe found associations in the expected direction, however this was lesser for Central/South America and Australia/New Zealand with roughly one third of findings in the expected direction. Studies which found mixed associations or associations in an unexpected direction were fairly prevalent in all countries while studies which had null findings made up a smaller, yet still substantial, proportion in all countries. Overall, there was no consistent pattern of association between built environment exposures and T2DM or weight status.

2.3.3 Discussion of literature review

The existing body of published scientific literature which investigates associations between the built environment and chronic health outcomes of T2DM and weight status was reviewed within this section. Overall, results demonstrate significant heterogeneity of findings. For all environmental exposures there was great variation in the metrics used, the context of the study, and the number and type of features used. Such heterogeneity and issues of reporting have been discussed in previous literature (Wilkins, Morris, Radley and Griffiths, 2017) and are problematic when trying to compare various studies. Given the current evidence base, it is notable that there are both inconsistent measurements of environmental exposures and inconsistent results of its relationship with the health outcomes in consideration.

There is a general consensus, and certainly a strong intuitive appeal, that the built environment plays an important role on individual and population health outcomes. Research on such associations has been largely focused on weight status as a health outcome, with much less focus on T2DM. This is a notable finding given that both health outcomes are posited to relate to environmental variables affecting diet and physical activity. A large body of scientific research has provided inconsistent evidence to support such hypotheses, however, and has thus failed to robustly identify direct causal mechanisms by which the built environment can influence health outcomes of T2DM and weight status.

Evidence demonstrated that the country, geographic measure, or varying built environment exposures considered did not affect the results. There may, however, be additional explanations for such outcomes including; heterogeneity in the environmental exposures used, limited generalisability between studies and countries, and individual mediators such as levels of physical activity and dietary habits. Furthermore, varying environmental exposures may either moderate, or may be moderated by, individual-level determinants. Compensatory behaviours are also important considerations. For example, people who use active transport may reduce physical activity in other parts of their life or may even consume more food than expected. Thus, it is important to understand where, when, why etc. people conduct health-related activities. Valid and reliable tools for such data acquisition are essential components of future research in this field. Future research may benefit also from the inclusion of a complex systems approach, the use of individual-level determinants as intermediary variables, and a more critical assessment of the methods used to represent both objective and perceived measures of the built environment.

Additionally, many studies were conducted within one region only however it may be valuable to assess such associations within wider regions to ensure a variety of environmental exposures and health outcomes are captured. The prevalent use of administrative units which may be ill-suited to examine associations between the built environment and health outcomes may also be an influential factor. Such units are subject to the modifiable areal unit problem (MAUP) and the Uncertain Geographic Context Problem (UGCoP – see Kwan, 2012). These concepts are a source of statistical bias whereby results are affected by spatial aggregation and delineation of data which may deviate from the true geographic context and therefore may misclassify relevant study areas (Kwan, 2012). Finally, few longitudinal studies and natural experiments mean that the field is over-reliant on associations which do not adequately account for endogeneity, self-selection, and temporal trends.

Strengths of the current review include inclusion of recently published articles and articles dating back over a decade, the inclusion of more than one health outcome, and the stratification of results by country and geographic measure. Limitations of the current review are largely centred on publication and reporting bias, which may influence not only what articles were available, but also the results included in articles. For example, authors may change the emphasis of their article based on which findings were significant, removing discussion of null or unexpected findings. Therefore other variables or relationships may remain unseen because they have not been reported on as extensively as significant findings. Thus, by excluding articles which assessed environmental exposures as mediating factors only the selection may be biased towards positive findings.

2.3.4 Section summary

The existing body of literature was reviewed in order to interpret the relevant evidence. Results are reflective of those found in previous reviews (den Braver et al., 2018; Feng et al., 2010; Mackenbach et al., 2014), yet this review provides an updated examination of studies which investigate associations between the built environment, T2DM, and weight status, including outcomes for children. The existing literature has been added to by considering multiple health outcomes and stratifying articles by country and geographic scale/measurement. Results of the current review demonstrated varying associations. This confirms that the existing body of research does not allow for a robust identification of the ways in which the built environment can influence T2DM and weight status.

2.4 Chapter summary

In conclusion, the aim of this review was to summarise the literature on the built environment, T2DM, and high weight status and discuss how geographical and spatial techniques are used within these fields of research. This literature review discusses the broader concepts of these topics and highlights the role of geospatial research techniques within such research. Therefore, this chapter aims to address Objective 1 (see Chapter 1, Section 1.3.1 on 'aims and objectives'), by comprehensively reviewing the current body of literature on spatial relationships between the built environment and health with a focus on T2DM and high weight status.

Overall, the evidence reviewing the nature of associations remains weak, suggesting a need for further research using nuanced measures and methods. Issues inherent within this type of research, identified through this literature review, are largely centred on the use of administratively defined aggregate areas and limited buffer sizes when assessing accessibility as well as an over-reliance on frequentist statistical methods which do not account for spatial or spatio-temporal interactions. Such issues have helped to shape this research and, in turn, this thesis aims to address these by employing methodological improvements in both the measurements of spatial accessibility and statistical methods using national level data. This is achieved through the use of Bayesian statistics and various techniques of measuring accessibility to the built environment, including an enhanced two-step floating catchment area model as well as standard administrative areas and both Euclidean and Network-based buffers, allowing for comparisons with previous research and sensitivity analysis. Future research should carefully consider the complexity of relationships between various aspects of the built environment and population health outcomes as well as the complexity of how these are measured and modelled.

Chapter 3 : The Aotearoa New Zealand context

3.1 Preface

Chapter 2 discussed the value of geospatial approaches for analysing relationships between the built environment and health. It highlighted the lack of research which considers multiple health outcomes and bought to light a gap in the current knowledge which is insufficiently addressed, namely the spatial context of diabetes in New Zealand. This chapter is intended to provide a context for the reader by discussing the geographic structure, population demographics, and healthcare system of Aotearoa New Zealand. Data used in this study falls into three broad categories: (1) geographic structure and population, (2) environmental exposures, and (3) health. The first category relates to both the population data and spatial scale used in this study, while the second relates to environmental exposures which are thought to have a putative association with health outcomes. Finally, health data considers both diabetes and childhood weight status. The first category will be covered in depth within the below section to outline the research area and context. Data relating to environmental exposures are covered in further depth in Chapter 4 and data relating to diabetes and childhood weight status in Chapters 5 and 6 respectively.

3.2 Geography and population

Aotearoa New Zealand is an island nation in the southwest of the Pacific Ocean. It is made up of two major landmasses: the North Island (Te Ika-a-Māui), and the South Island (Te Waipounamu). It also contains many smaller islands within its exclusive economic zone. This research focuses on the main urban areas of New Zealand only (Figure 3.1). There are two key reasons for this: (1) data on both health outcomes and environmental exposures is more reliable for urban areas, and (2) environmental exposures, population distributions, and geographic properties in New Zealand are relatively homogeneous within urban areas and therefore allow comparisons to be made. Such comparisons would not be valid for rural areas which have vastly different geographic properties and largely heterogeneous population structures.

3.2.1 Geography

Urban areas were defined using Statistics New Zealand (StatsNZ) Urban Areas Classification (2013a), Land Information New Zealand (LINZ) street electoral address data (2016), and Google Earth satellite imagery (2017). StatsNZ Urban Areas Classification (2013a) contains 150 categories which identify concentrated urban settlements via a hierarchical sub-division. Main urban areas given by this classification system are generally large and centred on a city; however, smaller urban areas may also be redefined by StatsNZ on the basis of population size or dependence on, and proximity to, main urban areas. Urban area boundaries within this classification are based on meshblocks, the smallest geographic unit of dissemination for New Zealand Census data (StatsNZ, 2013b), which can be aggregated to form larger geographic areas. Additionally, urban areas with little or no population were identified using LINZ street electoral address data (2016). This helped to further define the urban area classification based on geographic boundaries in addition to population density. Finally, to visualise the physical extent of urban areas, Google Earth satellite imagery (2017) was compared to the boundaries defined above. Thus, by considering multiple data sources this classification system retains only the most intensified urban areas (Figure 3.1, Appendix B).

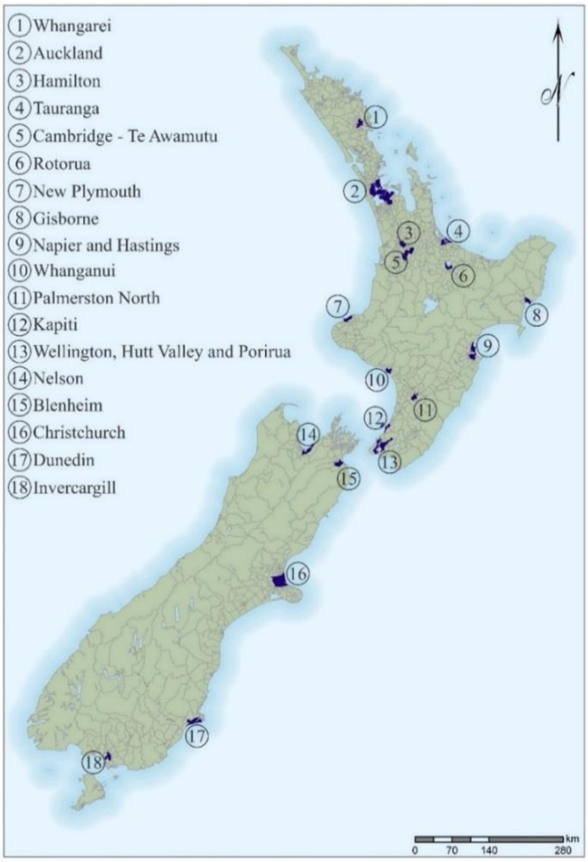


Figure 3.1: *New Zealand urban areas used in this study*

Meshblocks defined as urban using the above classification system were aggregated to Data Zone scale. Data Zones are geographic boundaries developed by Zhao and Exeter (2016) to minimise the effects of confidentiality within the Census data, while adhering to spatial and statistical criteria which ensures they are robust for analysis. Data Zones are intermediary sized areas which fall between meshblock and census area unit scales, containing an average population of 712 (range 501 - 999). A comparison of these geographic scales is shown in Figure 3.2 where there is one census area unit which contains eight Data Zones (intermediary scale), and 52 meshblocks (finest scale).

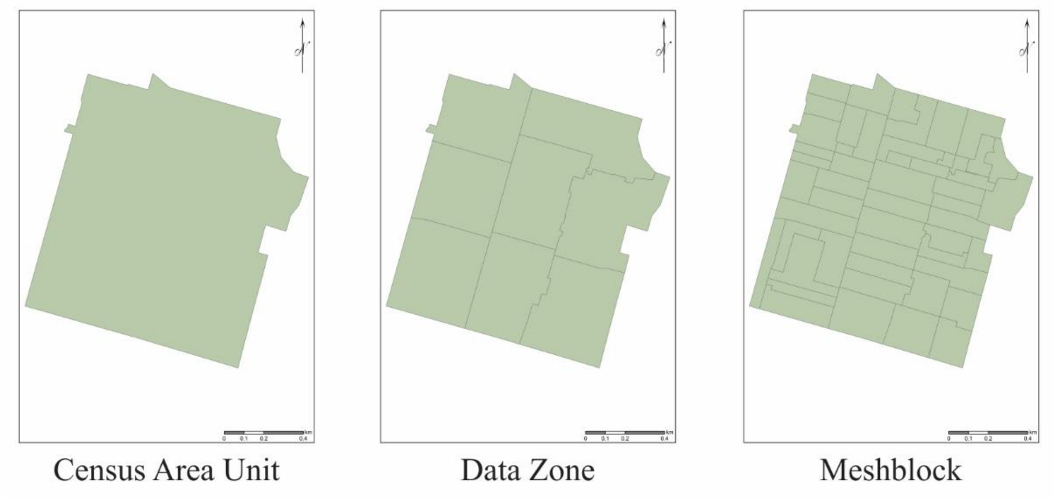


Figure 3.2: *Variations in geographic scale*

Data Zones are based on six criteria for health and social research which are commonly used for zone design; geographic contiguity, respecting administrative boundaries, respecting physical barriers, population distribution, socioeconomic homogeneity, and compactness (Zhao and Exeter, 2016). These features support the use of Data Zones as a statistical and geographic base for analysis, by which more accurate and reliable results can be achieved than based on standard Census administrative boundaries alone. For example, New Zealand small area research typically uses pre-defined administrative boundaries, based on the Census, including meshblocks (population range 0 – 1,500+) or census area units (population range from 0 – 9,000+). There are statistical issues with both of these geographic scales which may skew analysis or render results unreliable, ranging from null populations in smaller meshblocks to populations with heterogeneous attributes in larger census area units. The creation and subsequent use of Data Zones represents a significant development in socio-spatial research within New Zealand as it enables researchers to move beyond relying on geographic areas based solely on Census boundaries, which are predominately designed for data collection purposes. Of a total 5,958 Data Zones nationwide, 4,089 were classified as urban areas in this study (Table 3.1), with the three largest contiguous areas being Auckland, Wellington, and Christchurch. These urban Data Zones were comprised of 27,367 meshblocks, 1,293 less than that given by StatsNZ Urban Areas Classification (2013a), as some meshblocks were removed because they either did not fully comprise a Data Zone or were not considered as completely urban, based on the additional classification sources. Maps will be presented for Auckland, Wellington, and Christchurch throughout the main body of the text while maps for all other urban areas are contained within relevant appendices.

Table 3.1: *Main urban area details*

	Usually Resident Population (2013)	Number of Data Zones
Auckland	1,251,714	1,697
Wellington	189,273	270
Christchurch	340,059	480
Other Urban – North Island: *Cambridge, Gisborne, Hamilton, Hastings, Kapiti, Hutt Valley, Napier, New Plymouth, Palmerston North, Porirua, Rotorua, Tauranga, Te Awamutu, Whanganui, Whangarei*	915,942	1,299
Other Urban – South Island: *Blenheim, Dunedin, Invercargill, Nelson*	248,508	343
TOTAL	2,945,496	4,089

Source: The University of Auckland. New Zealand Data Zones developed by Zhao and Exeter 2016 and licensed by The University of Auckland for re-use under the Creative Commons Attribution 3.0 New Zealand Licence

3.2.2 Population

In regard to population demographics, New Zealand is home to approximately 4.5 million people. Given a land area of 268,021 km^2 this means that it has a relatively low population density, roughly 15 people per square kilometre, compared to other developed nations and areas with significant population numbers are generally highly urbanised. Indigenous Māori inhabited New Zealand as early as the thirteenth century, with European explorers arriving in the seventeenth and eighteenth centuries (Orange, 2011). In 1840, with the signing of the Treaty of Waitangi, Aotearoa New Zealand became a formal British colony (Orange, 2011). In the modern day it is an ethnically diverse country, with approximately one quarter of residents born overseas, and the most prominent ethnic groups including New Zealand European, Māori, and Pacific Peoples. New Zealand European is generally considered New Zealand citizens who are of European descent. Statistics for this group also typically include a combination of ‘other’, smaller ethnic groups. Māori are the indigenous inhabitants and Pacific Peoples are considered as people from the other islands of the Pacific Ocean. Both of these ethnic groups are disproportionately located in highly deprived areas and are generally shown to have poorer health outcomes than the national population (Ministry of Health, 2016b). All population data, including gender, age, and ethnicity, were sourced at Data Zone scale and the total usually resident population for each urban area is shown in Table 3.1. The base population used for Data Zones is based on Census (2013c) data, random rounded to base 3, where Data Zones with fewer than five people in each demographic group are confidentialised.

3.3 Socioeconomic status

While the geographic composition of the country is an important aspect of this research, it is also worth noting briefly the social context of New Zealand. The socioeconomic status (SES) of Data Zones was defined using the Index of Multiple Deprivation (IMD) developed by Exeter et al. (2017). It is argued that this offers an advance on previous measures of socioeconomic status in New Zealand whereby deprivation is based on 28 indicators categorised into seven domains: employment, income, crime, housing, health, education, and access (Exeter et al., 2017). While previous deprivation measures, such as the New Zealand Deprivation Index (NZDep) (Atkinson, Salmond & Crampton, 2014), have provided an overall measure of socioeconomic status, more detailed information on the social gradient of urban areas can be gained using the IMD. For example, the above-mentioned measures may be used individually, or in combination, to give a detailed exploration of socioeconomic deprivation in New Zealand at Data Zone scale. For this study, the IMD measure without the ‘access’ domain was used for all analysis. This is primarily due to the similarity, and potential collinearity (where variables are highly correlated or can predict one another), between some of the measures used to construct this domain of deprivation and the environmental exposures used in this research.

3.4 Healthcare system

New Zealand’s healthcare system is multifaceted, consisting of a publically funded/subsidised system and a private system. Hospital care, general practitioners (GPs), community care facilities, and some pharmaceuticals fall into the former of these categories and are centrally monitored by the government’s Ministry of Health. The Ministry of Health distributes funding and resources to twenty District Health Boards (DHBs) throughout the country, who are then responsible for service provision in their respective region. This is largely implemented through Primary Healthcare Organisations (PHOs[3]) which can differ between regions depending on the size of the geographic area and population structure. People who access any of these publically funded or subsidised services are assigned a National Health Index (NHI) number which is unique to each user and does not change throughout their lifetime (Ministry of Health, 2017a). This NHI number can then be utilised to identify each time the user accesses any type of healthcare through the system. Furthermore, the NHI database retains information about each unique user including date of birth, ethnicity, gender, and residential information. This can be used for both monitoring and research purposes and formed the basis of health datasets used in this research, emphasizing the increasingly important role of technology and big data management within New Zealand’s health sector.

3.5 Chapter summary

In conclusion, the purpose of this chapter was to provide contextual information about Aotearoa New Zealand for the reader. This includes not only detailing its geographic structure but also population demographics, socioeconomic status, and the healthcare system. This chapter contributes, in part, to Objective 1 (see Chapter 1, Section 1.3.1 on ‘aims and objectives’), by providing a contextual foundation for the reader. It is apt to finish this chapter by noting that studies should carefully consider not only the country-specific geography, but also the influence of population demographics and socioeconomic status in order to ensure robust research.

[3] PHOs are funded by DHBs and provide primary healthcare services through provider members such as general practices.

Chapter 4 : Modelling built environment exposures and investigating associations with socioeconomic deprivation

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4.1 Preface

Chapter 3 outlined the Aotearoa New Zealand context. The aim of the current chapter is to create explore various ways of measuring built environment exposures and investigate relationships with socioeconomic deprivation. This is the first of three analytical chapters, all of which utilise GIS and geospatial methods. Within this chapter such methods are used to understand relationships between the built environment and socioeconomic deprivation, while chapters five and six focus on understanding relationships between the built environment and chronic health conditions. This chapter begins with a short introduction before discussing the methods and results, then concludes with a discussion and summary.

4.2 Introduction

At an ecological level, population exposure to environments where food is low in cost and nutrient quality and physical activity is not supported, often called obesogenic environments (Swinburn et al., 2011), are a possible explanation for socio-spatial variations in health outcomes. While demographic, socioeconomic and contextual relationships surrounding health, diet and physical activity are complex, supportive environments are said to be fundamental in shaping people’s choices (Swinburn et al., 2011). The human body exhibits good physiological defences against energy depletion, however, it has been noted that defences are weak against excess energy accumulation, particularly when highly palatable food opportunities are abundant (Lowe et al., 2009). Furthermore, such environmental barriers may undermine individual motivations to change unhealthy behaviours and habits. Obesogenic environments have been related to socioeconomic status, having negative health effects through several pathways such as impeded engagement in healthy behaviours, limited education on nutrition, and limited financial and geographic access to resources (Fraser et al., 2010). Research between built environment exposures and socioeconomic deprivation is centred on the deprivation-amplification hypothesis whereby populations living in highly deprived areas experience further disadvantage in access to health-promoting resources (Macintyre, Macdonald, & Ellaway, 2008; Schneider, D’Agostino, Weyers, Diehl & Gruber, 2015). Common contextual representations of diet-related exposures within the built environment are accessibility and density of food outlets (Feng et al., 2010; Fraser et al., 2010; Thornton et al., 2012). Additionally, pathways for physical activity within the built environment include access to facilities for physical activity, open spaces for recreation and greenspace (Townshend & Lake, 2009). These do not, however, consider other aspects of diet and activity related exposure such as advertising and sociocultural norms.

The food environment is the physical, economic and sociocultural surroundings, opportunities and conditions which can influence population choices (Lake & Townshend, 2006; Swinburn et al., 2011), as discussed in Section 2.2.1. These environments vary greatly and are shaped by the distribution of food retailers by type, price and quality. Food environments are constantly evolving, although not always equally. Socially stratified spatial patterning of unhealthy outlets may be explained by greater demand, little civic resistance to new developments, and lower land use costs for businesses in more deprived areas (Fraser et al., 2010). Research on food environments conducted within North America demonstrates clear spatial patterns between areas where there is little or no access to healthy foods – 'food deserts', socioeconomic status and health (Moore & Diez Roux, 2006; Morland, Wing, Diez Roux & Poole, 2002; Smoyer-Tomic et al., 2008; Walker et al., 2010). In other settings, relationships have not been as clear with research showing mixed results and in many cases demonstrating higher concentrations of outlets, both healthy and unhealthy, in highly deprived areas – 'food swamps' (Duran et al., 2013; Feng et al., 2010; Macdonald, Ellaway & Macintyre, 2009; Macintyre, McKay, Cummins & Burns, 2005; Macintyre et al., 2008; Maguire, Burgoine & Monsivais, 2015; Maguire, Burgoine, Penney, Forouhi, & Monsivais, 2017; Pearce, Blakely, Witten & Bartie, 2007; Pearce et al., 2008a; Pearce, Witten, Hiscock & Blakely, 2008b; Sushil, Vandevijvere, Exeter & Swinburn, 2017; Svastisalee et al., 2011). Research on the physical activity environment has also shown mixed results and is largely dependent on the methods and measures used, of which there is significant variation (Hill, Chau, Luebbering, Kolivras & Zoellner, 2012; Jones, Hillsdon, & Coombes, 2009**;** Pearce et al., 2008b; Schneider et al., 2015). Current research findings, while mixed, indicate that contextual associations between the built environment and socioeconomic status may help to explain unequal spatial variations in negative health outcomes. Geographic variation in local environments can thus be an important contributor to population health which requires further research.

In New Zealand, Pearce et al. (2007) was the first study to use a GIS-based methodology to examine accessibility to food environments. They found a strong association between deprivation and geographic accessibility. Furthermore, research by Pearce et al. (2008a) analysed the role of neighbourhood access to provision of healthy and affordable food, again finding that access to a range of retail options was better in highly deprived areas. More recently, Sushil et al. (2017) has also confirmed the findings of Pearce et al. (2007; 2008a), demonstrating that food swamps in New Zealand are stratified by deprivation. Research using a GIS framework has used many different measures and contextual variables however, making comparisons difficult. This heterogeneity was discussed in more detail within the previous literature review. This study builds on previous GIS-based research (Pearce et al., 2008a) which analysed relationships between the built environment and deprivation, using nuanced methods of spatial measurement and a robust spatial scale, to further understand such relationships within urban New Zealand.

4.3 Methods

4.3.1 Data

Data on spatial scale, population, and socioeconomic status have been discussed previously (Chapter 3). Within this study the term 'exposure' refers to six categories (Table 4.1).

Table 4.1: *Study categories and details*

Study Category	Description	Data Source
Fast Food	Multinational franchises	Ministry for Primary Industries Territorial Authorities
Takeaways	National businesses	Ministry for Primary Industries Territorial Authorities
Dairy/Convenience	Retailers of pre-packaged convenience foods. Includes dairy, convenience, superette, service stations, small grocers	Ministry for Primary Industries Territorial Authorities
Supermarket	Supermarket franchises	Ministry for Primary Industries Territorial Authorities
Fruit/Vegetable	Includes fruit/vegetable stores, produce retailers, green grocers	Ministry for Primary Industries Territorial Authorities
Activity Facilities	Facilities for physical activity/recreation. Includes gym, fitness centre, sports hall, tennis, rugby, swimming, soccer, bowls, golf, hockey, cricket, martial arts, rowing	Territorial Authorities Zenbu Directory
Greenspace	Grass, garden or vegetation (public belonging to the Crown, or private)	Beere & Kingham (2017)

In the context of this study, the study categories given in Table 4.1 above are considered as environmental exposures, representing various aspects of the built environment. These may be referred to as such within the following chapters. Fast food, takeaways, and dairy/convenience stores are considered as unhealthy exposures which reflect aspects of the built environment which can be detrimental to health. In contrast, supermarkets, fruit/vegetable stores, activity facilities, and greenspace are considered as healthy exposures which reflect aspects of the built environment which can be health-promoting. This categorisation is consistent with previous research (refer to Appendix A).

Data on the above exposures aspects of the built environment was collected from four data sources: Ministry for Primary Industries (MPI); Territorial Authorities (TAs) which are the second tier of local government in New Zealand; Zenbu business directory[4]; and Beere & Kingham (2017). Details of these sources are explained in the following sections. The primary sources of data were MPI and TAs due their frequent updating and reliability. Zenbu business directory was used as a data source for one category only, activity facilities, as these are not required to be systematically registered through either of the former two government bodies. Finally, data from Beere and Kingham (2017) was used to represent national greenspace, both public and private.

MPI is responsible for registering all large, multinational food franchises including fast food chains and supermarkets. Following the Food Act (2014) all businesses that manufacture, prepare, or sell food or food products are required to be registered through the Food Control Programme (FCP). They are also required to have their data on MPI's public register by the end of 2019, which is largely the responsibility of the relevant TA. Data on business registrations was collected from two MPI sources in August of 2017; the FCP (MPI, 2016a) which registers businesses under the Food Act 2014, and the Food Safety Programme (FSP) which holds data on businesses registered under the Food Act (1981) which have not transitioned to the new register (MPI, 2016b). Sectors included in this study were the food service sector and food retailers. Sectors not included relate primarily to the nature of the business such as manufacturers and processers, which are not of interest in this study. Records with a valid registration date were kept from the FSP, which were then combined with data collected from the FCP to create the final MPI dataset.

[4] https://www.zenbu.co.nz

The transition of businesses to the FCP only started being enforced from March 2016, with many TAs yet to upload their data, so TAs were also contacted individually to ensure a comprehensive dataset. The second source of data, TAs, are comprised of 67 different governing bodies; 13 city councils, 53 district councils, and the Chatham Islands Council[5]. Data on health licenses from 2013 - 2015, which include food producers and retailers, were requested from 66 territorial authorities (the Chatham Islands were excluded due to the remote nature of their geography), and pre-defined categories of business were given by 89.6%. Where given, these were used to re-categorise the exposure into the categories listed in Table 4.1. If the business category was not given, however, the business name was used to categorise the exposure, with ambiguous names investigated in further detail or excluded if a category could not be clearly defined. Categories given that were not included in the study re-categorisation were as follows: mobile premise, stall, bakery, café, restaurant, childcare, education, beverage, bar, tavern, hotel, caterer, delivery only, dessert, theatre, cinema, hospital, bistro, club, market, funeral director, post, brewery, honey/apiaries, food processing, internet, motel, lodge, camp ground, butcher/deli, fish/meat, retail, wholesale, sale and supply of alcohol, refreshment room, warehouse, offensive trade, manufacture, storage, church, conveyance/ transport. TA data has been used in most research which investigates environmental exposures in New Zealand (Pearce et al., 2007; Pearson et al., 2014; Sushil et al., 2017). Yet, many TAs noted that they had either already uploaded data to the FCP or that their data was incomplete given that they do not register many of the larger multinational chains which, as discussed, is the responsibility of MPI. Therefore a combination of sources were used to allow for a comprehensive dataset.

As shown in Figure 4.1, all closed premises from MPI and TA sources were removed. If duplicates entries for one premise were given, only the latest registration was kept, however, duplicate business names for current registrations at different locations were kept as unique records. Notably, there are a substantial number of duplicates (Figure 4.1), as some TAs provided data for all years and therefore the same premises were entered every year, yet only the most recent was kept. Premises with insufficient spatial information, meaning those which did not have a street address and could not be geocoded accurately, were removed before the two datasets were combined. Duplicates were then removed to create the final study categories (Figure 4.1). The third source of data, Zenbu, is a crowd-sourced business

[5] The Chatham Islands are located approximately 800 kilometres east of the South Island, forming an archipelago in the Pacific Ocean.

directory. Records date from 2006 containing more premises in total, but included closed premises, compared to the formerly discussed datasets. Therefore, it is assumed that an up-to-date dataset would be smaller than the one sourced. Zenbu also did not have many of the premises registered with government bodies, further suggesting it is incomplete. These factors indicate the unacceptable level of uncertainty in the Zenbu dataset. For this reason the Zenbu dataset was used for the activity facilities category only, where only a small amount of data was available from government bodies. Zenbu contained 922 records on activity facilities, however, 67 were removed due to duplication with the government datasets. The final activity facilities category consisted of 1,186 records in total; 331 from government datasets and 855 from Zenbu.

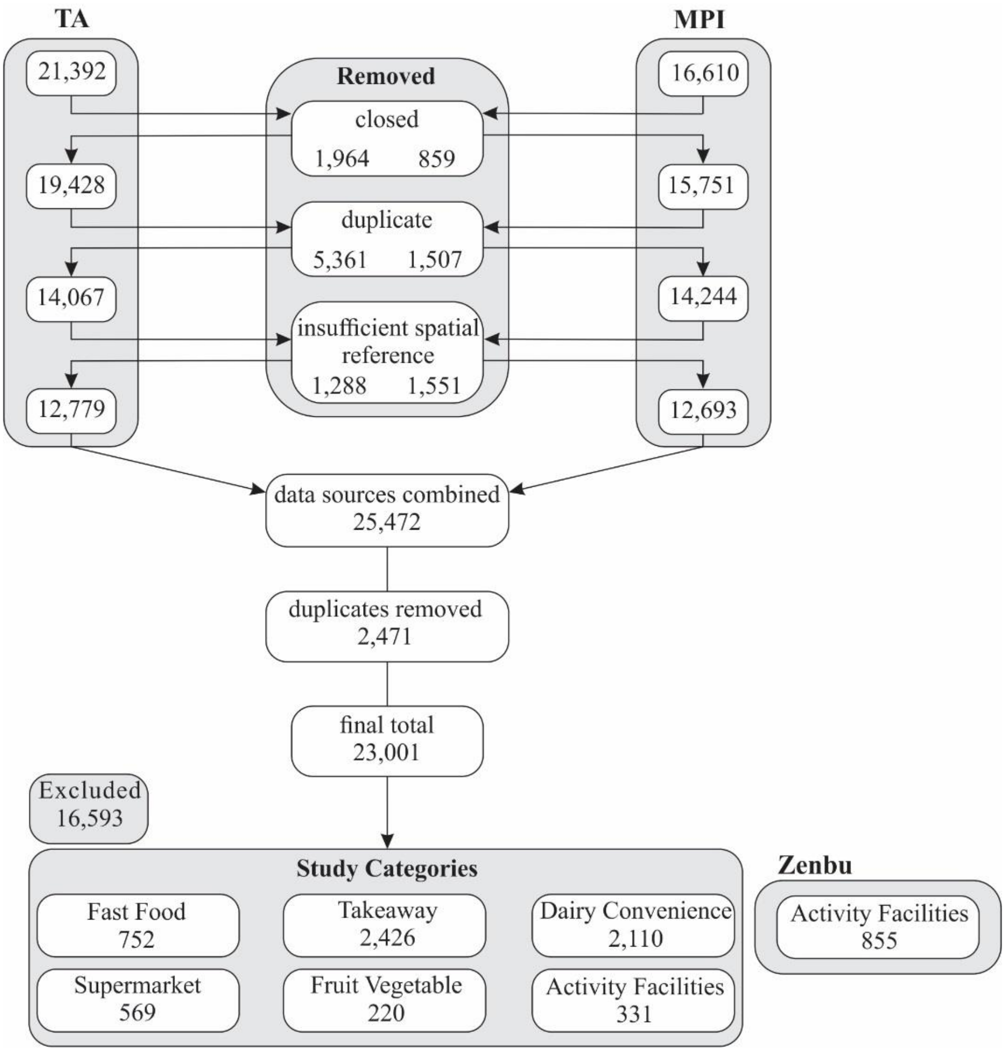

Figure 4.1: *Data eligibility and study categorisation*

The final ‘study categories’ data (Figure 4.1) were geocoded using Google Maps Application Programming Interface (API), at the address level of precision, and the geographic coordinates for any un-matched records were manually looked up. In total, 0.62% (N = 45) of premises included in the final study categories did not have sufficient spatial information to be accurately geocoded.

The fourth, and final, source of environmental exposures data relates to greenspace. Data on greenspace was sourced from Beere and Kingham (2017) in the form of a GIS layer. This layer was adapted and updated, using Land Cover Database (LCDB3.3), from a previously constructed layer by Richardson, Pearce, Mitchell, Day and Kingham (2010). Richardson et al. (2010) initially used three nationwide datasets (Land Cover Database (LCDB2), Department of Conservation Boundaries (2003), and Land Information New Zealand’s Core Record System (2004) in the construction of this GIS layer to represent both public and private greenspace nationally.

4.3.2 Analysis

To assess relationships between urban populations and environmental exposures listed in Table 4.1, population-weighted centroids for Data Zones (discussed in Section 3.1) were created using latitude and longitude coordinates of LINZ (2016) electoral address points. Each address was mapped and the ‘mean centre’ tool in ArcGIS was used to create a centroid based on the location of all addresses within each Data Zone. This more accurately reflects where a population is living than a geometric centroid. This has important implications when considering, for example, Data Zones with a large area of which only a small percentage is inhabited. This study considers various measures of spatial accessibility including Euclidean-based and Network-based buffers, of varying sizes, and an Enhanced Two-Step Floating Catchment Area (E2SFCA) model. Multiple measures were used in order to compare results and judge the sensitivity of results based on the choice of metric as well as ensure that this analysis is comparable to previous research.

Analysis was undertaken in four stages. First, usually resident population and the number of each point-based environmental exposure category were extracted for deprivation quintiles to calculate the rate per 1,000 population by Data Zone. Pearson’s two-tailed correlation was used to assess the direction and the extent of relationships. Secondly, buffers were used to investigate the relationship between environmental exposures and deprivation. ArcGIS version 10.4.1 (ESRI, 2011) was used to construct Euclidean-based buffers of 800, 1600, and

3000 metres around population-weighted centroids. These ranges were informed by previous research: 800 metres reflects an average walking distance, 1600 metres reflects one mile (a common intermediary buffer size), and 3000 metres reflects a typical driving distance (Feng et al., 2010; Pearce et al., 2008a). Euclidean-based buffers are only one interpretation of spatial scale however and face issues when considering how people actually travel and move around in geographic space. Euclidean-based buffers take a direct line of spatial measurement which is not always practical when considering how a city is built up. For this reason, Network-based buffers were also created to measure buffer distances through a road network layer (Beere, 2016). This is a practical measurement of what geographic space in an urban area is like, reflected through road network connections and measurements. Network-based buffers are generally smaller than Euclidean-based and therefore capture less total exposures. A comparison of these buffer sizes and types can be seen (Figure 4.2). For each of the above-mentioned measures of spatial accessibility, the count and proportion of each environmental exposure category was calculated for data-driven bins and stratified by deprivation quintile.

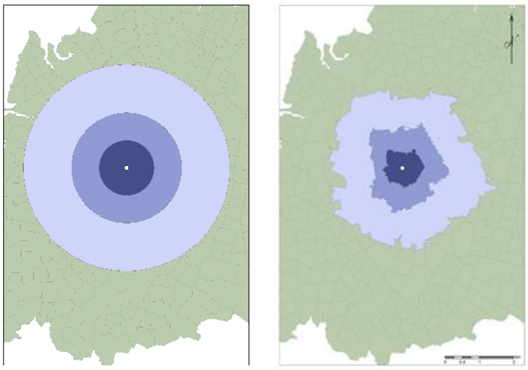

Figure 4.2: *Example of Euclidean-based and Network-based buffers*

The third stage of analysis employed an E2SFCA model (Kwan, 1998; Luo & Qi, 2009) to assess spatial accessibility. This method was chosen as it enables a measure to be used which is based on proximity to exposures and incorporates how influential these may be based on distance. For this method travel time in minutes, via motor vehicle and the road network, from each population-weighted centroid to the nearest five of each environmental exposure was calculated and Gaussian-weighted using ArcGIS version 10.4.1 (ESRI, 2011). Although there are no set standards regarding the number of destinations, five destinations were used so that the likelihood of capturing the actual population service choice increases while also ensuring that each area has enough of each environmental exposure to model these accurately. Exposures were weighted according to a Gaussian distribution so that those in closer proximity to population-weighted centroids were considered more influential than those which were further away. This study treats each exposure as having a capacity of one, therefore the final weighted sum ranges from 0 – 5, representing areas with lowest to highest spatial accessibility. Maps were created to visualise results and the count and proportion of each environmental exposure category was calculated and stratified by deprivation quintile.

Finally, to measure greenspace the percentage of both public/private greenspace within each buffer was calculated, consistent with prior research (Beere & Kingham, 2017), and Pearson's correlation used to assess relationships with socioeconomic status. Notably, greenspace is separated from other environmental exposures as it is a polygon layer. Because of this differentiation, greenspace was not subject to the same procedure as the other study categories, and measures of greenspace were limited to analysis that used buffers only.

4.4 Results

The relationship between the number of exposures per 1,000 population and deprivation for main urban areas of New Zealand shows a clear social gradient (Table 4.2), with the most deprived areas having a higher ratio of all environmental exposure when compared to the least deprived areas, particularly fast food outlets. All other exposures are also shown to be more prevalent in more deprived areas but to a lesser degree, with activity facilities demonstrating the lowest ratio (Table 4.2). Furthermore, Pearson's correlation coefficients are statistically significant ($p < 0.10$) across all deprivation quintiles for all environmental exposures apart from activity facilities (Table 4.2).

Table 4.2: *Rate of exposures per 1,000 population (2013) by deprivation quintile*

	Deprivation Quintile							
	Q1 Lower	Q2	Q3	Q4	Q5 Higher	Ratio Q5:Q1	r^a	*P*-Value
Fast Food	0.04	0.19	0.19	0.33	0.27	7.45	.870	.055
Takeaway	0.20	0.60	0.64	0.94	0.76	3.83	.845	.072
Dairy/Convenience	0.17	0.40	0.50	0.66	0.67	4.02	.962	.009
Supermarket	0.05	0.08	0.12	0.16	0.13	2.57	.878	.050
Fruit/Vegetable	0.02	0.03	0.06	0.07	0.06	3.17	.875	.052
Activity Facilities	0.17	0.24	0.29	0.33	0.26	1.53	.714	.175

[a]Pearson's correlation coefficients

Although the results in Table 4.2 tend to show a higher prevalence of all exposures in deprived areas, this analysis considers exposures within Data Zone boundaries only and provides a limited interpretation of the relationship with deprivation. Therefore, the next stage of analysis examined the relationship between socioeconomic status and exposures using buffer analysis.

4.4.1 Spatial accessibility: Euclidean and network-based buffers

Over half of the Data Zones in the main urban areas of New Zealand do not have a fast food outlet within an 800 metre Euclidean-based radius with little differentiation between the most and least deprived areas (Table 4.3). For Data Zones with one or more fast food outlets, however, the ratio of Data Zones in quintile 5 compared to quintile 1 is above one, showing a higher proportion of areas with access to one or more fast food outlets in more deprived areas. Takeaway outlets reflect a similar pattern except that highly deprived areas are roughly 25% less likely to have 0 outlets. Additionally, as the number of takeaway outlets increases so too does the ratio between the most and least deprived areas (Table 4.3). Results for dairy/convenience are broadly consistent with previous categories where highly deprived areas are almost three times as likely to have 3 or more dairy/convenience stores compared to less deprived areas (Table 4.3). Generally, there are a greater proportion of areas with no outlets in less deprived areas and a greater proportion of areas with one or more outlets in highly deprived areas. Furthermore, highly deprived areas are shown to be over three times as likely to have 3 or more supermarkets and four times as likely to have 2 or more fruit/vegetable stores as the least deprived areas (Table 4.3). The pattern for activity facilities is more mixed than for other environmental exposure categories however and does not show a distinct social gradient.

Table 4.3: *Deprivation and exposures within an 800m Euclidean buffer*

	Deprivation Quintile						
No. of outlets	Q1 Lower	Q2	Q3	Q4	Q5 Higher	Total	Ratio Q5:Q1
Fast Food							
0	22.7 (603)	17.8 (472)	19.3 (513)	18.2 (484)	22.0 (583)	100 (2655)	0.97
1	16.6 (113)	18.3 (124)	18.7 (127)	23.4 (159)	23.0 (156)	100 (679)	1.38
2	6.8 (18)	17.9 (47)	21.7 (57)	31.2 (82)	22.4 (59)	100 (263)	3.28
3+	8.9 (44)	20.7 (102)	22.6 (111)	25.2 (124)	22.6 (111)	100 (492)	2.52

Table 4.3: *Deprivation and exposures within an 800m Euclidean buffer … continued*						
Takeaway						
0	27.7 (418)	19.8 (299)	17.4 (263)	14.2 (214)	20.9 (316)	100 (1510)	0.76
1	17.5 (145)	18.8 (156)	20.1 (167)	21.1 (175)	22.5 (187)	100 (830)	1.29
2	18.7 (92)	15.1 (74)	21.8 (107)	21.2 (104)	23.2 (114)	100 (491)	1.24
3	12.5 (41)	15.6 (51)	20.5 (67)	26.9 (88)	24.5 (80)	100 (327)	1.95
4	10.2 (24)	19.9 (47)	19.5 (46)	28.0 (66)	22.5 (53)	100 (236)	2.21
5+	8.3 (58)	17.0 (118)	22.7 (158)	29.1 (202)	22.9 (159)	100 (695)	2.74
Dairy/Convenience							
0	28.1 (396)	19.4 (273)	18.5 (260)	15.1 (212)	18.9 (266)	100 (1407)	0.67
1	18.7 (187)	16.6 (166)	21.8 (218)	20.6 (206)	22.2 (222)	100 (999)	1.19
2	17.0 (99)	19.8 (115)	19.8 (115)	19.4 (113)	23.9 (139)	100 (581)	1.40
3+	8.7 (96)	17.3 (191)	19.5 (215)	28.9 (318)	25.6 (282)	100 (1102)	2.94
Supermarket							
0	21.4 (577)	18.3 (492)	18.8 (505)	19.1 (513)	22.4 (603)	100 (2690)	1.05
1	15.4 (172)	18.2 (203)	21.7 (242)	23.7 (264)	21.1 (235)	100 (1116)	1.37
2	10.7 (24)	18.3 (41)	21.0 (47)	25.9 (58)	24.1 (54)	100 (224)	2.25
3+	8.5 (5)	15.3 (9)	23.7 (14)	23.7 (14)	28.8 (17)	100 (59)	3.40
Fruit/Vegetable							
0	20.5 (730)	18.7 (664)	19.0 (677)	19.9 (708)	21.8 (776)	100 (3555)	1.06
1	9.5 (44)	12.6 (58)	26.0 (120)	26.6 (123)	25.3 (117)	100 (462)	2.66
2+	5.6 (4)	31.9 (23)	15.3 (11)	25.0 (18)	22.2 (16)	100 (72)	4.00
Activity Facilities							
0	21.0 (414)	17.9 (353)	17.9 (353)	18.6 (368)	24.7 (487)	100 (1975)	1.18
1	17.7 (195)	16.3 (180)	21.1 (232)	22.7 (250)	22.2 (244)	100 (1101)	1.25
2	19.8 (100)	19.4 (98)	20.2 (102)	22.6 (114)	18.0 (91)	100 (505)	0.91
3+	13.6 (69)	22.4 (114)	23.8 (121)	23.0 (117)	17.1 (87)	100 (508)	1.26

Table shows the proportion and count (in parentheses) of Data Zone with 1, 2, 3 etc. exposures within 800 metres (Euclidean-based measure) of the population-weighted centroid, stratified by deprivation quintile

Using larger sized buffers of 1600 metre and 3000 metre captured a greater number of exposures. The 1600 metre Euclidean-based buffer shows similar patterns for takeaway and dairy/convenience exposure categories as the previous results (Table 4.4). This is also reflected in both supermarket and fruit/vegetable exposure categories for this buffer which differs slightly from the 800 metre buffer where highly deprived areas had higher ratios for all numbers of outlets. While showing a similar pattern to the 800 metre buffer, this indicates that as the buffer size is extended and more outlets are captured, the social gradient by which highly deprived areas have more supermarkets and fruit/vegetable stores is further illustrated (Table 4.4).

The pattern for activity facilities differs from the 800 metre buffer, showing a steady decline whereby there are more areas in the most deprived quintile which have 0 facilities and less which have greater numbers of facilities compared to the areas in the least deprived quintile (Table 4.4). The pattern in fast food exposures also changes when considering a larger buffer size (1600 metre), as areas in more deprived quintiles are now shown to have higher proportions of areas with 0 - 5 and 6 - 10 fast food outlets but smaller proportions of areas with 11 or more outlets compared to least deprived areas (Table 4.4).

Table 4.4: *Deprivation and exposures within a 1600m Euclidean buffer*

	Deprivation Quintile						
No. of outlets	Q1 Lower	Q2	Q3	Q4	Q5 Higher	Total	Ratio Q5:Q1
Fast Food							
0 - 5	20.8 (696)	17.8 (596)	19.1 (637)	19.8 (661)	22.5 (752)	100 (3342)	1.08
6 - 10	10.6 (61)	16.2 (93)	22.0 (126)	26.4 (151)	24.8 (142)	100 (573)	2.34
11+	12.1 (21)	32.2 (56)	25.9 (45)	21.3 (37)	8.6 (15)	100 (174)	0.71
Takeaway							
0 - 5	24.6 (537)	19.2 (419)	18.2 (398)	15.9 (346)	22.1 (481)	100 (2181)	0.90
6 - 10	14.6 (126)	15.0 (130)	19.4 (168)	26.3 (227)	24.7 (213)	100 (864)	1.69
11+	11.0 (115)	18.8 (196)	23.2 (242)	26.4 (276)	20.6 (215)	100 (1044)	1.87
Dairy/Convenience							
0 - 5	23.0 (580)	18.7 (471)	19.2 (485)	17.9 (451)	21.2 (536)	100 (2523)	0.92
6 - 10	16.6 (121)	16.1 (117)	20.1 (146)	22.4 (163)	24.9 (181)	100 (728)	1.50
11+	9.2 (77)	18.7 (157)	21.1 (177)	28.0 (235)	22.9 (192)	100 (838)	2.49
Supermarket							
0	24.7 (245)	17.5 (173)	18.1 (179)	17.2 (170)	22.5 (223)	100 (990)	0.91
1	20.0 (290)	20.2 (294)	20.0 (290)	19.5 (283)	20.4 (296)	100 (1453)	1.02
2	14.4 (129)	16.1 (144)	21.6 (193)	23.9 (214)	23.9 (214)	100 (894)	1.66
3+	15.2 (114)	17.8 (134)	19.4 (146)	24.2 (182)	23.4 (176)	100 (752)	1.54

Table 4.4: Deprivation and exposures within a 1600m Euclidean buffer … continued							
Fruit/Vegetable							
0	22.1 (563)	19.3 (492)	18.6 (475)	19.3 (491)	20.7 (526)	100 (2547)	0.94
1	15.4 (160)	15.9 (165)	23.8 (247)	22.1 (230)	22.9 (238)	100 (1040)	1.49
2+	11.0 (55)	17.5 (88)	17.1 (86)	25.5 (128)	28.9 (145)	100 (502)	2.63
Activity Facilities							
0 - 5	19.9 (625)	16.9 (531)	18.7 (589)	20.0 (628)	24.6 (774)	100 (3147)	1.24
6 - 10	16.6 (121)	21.0 (153)	21.7 (158)	25.4 (185)	15.4 (112)	100 (729)	0.93
11+	15.0 (32)	28.6 (61)	28.6 (61)	16.9 (36)	10.8 (23)	100 (213)	0.72

Table shows the proportion and count (in parentheses) of Data Zone with 1, 2, 3 etc. exposures within 1600 metres (Euclidean-based measure) of the population-weighted centroid, stratified by deprivation quintile

The 3000 metre Euclidean-based buffer reflects a similar pattern to that of the 1600 metre buffer for activity facilities, where highly deprived areas are roughly 25% less likely to have 21 or more activity facilities while they are 25% more likely to have no activity facilities compared with areas in less deprived quintiles (Table 4.5). Reflecting the pattern of the 800 metre Euclidean-based buffer, areas in highly deprived quintiles are again more likely to have both smaller and greater numbers of supermarkets and fruit/vegetable stores. Areas in more deprived quintiles are shown to have significantly higher proportions of areas with large numbers of fruit/vegetable stores (6 or more), at over 2 and a half times that of areas in less deprived quintiles (Table 4.5).

As with the 1600 metre Euclidean-based buffer, highly deprived areas have slightly higher proportions of areas with 0 - 10 and 11 - 20 fast food outlets, but actually slightly less areas with 21 or more fast food outlets in less deprived quintiles (Table 4.5). The dairy/convenience category reflects a similar pattern to that of smaller buffers (Table 4.5). The takeaway category is slightly more mixed when considering the largest Euclidean-based buffer with results demonstrating that areas in highly deprived quintiles are more likely to have lower (0 - 20) and mid-range (21 - 40) proportions of outlets when compared to areas in less deprived quintiles (Table 4.5).

Table 4.5: *Deprivation and exposures within a 3000m Euclidean buffer*

	Deprivation Quintile						
No. of outlets	Q1 Lower	Q2	Q3	Q4	Q5 Higher	Total	Ratio Q5:Q1
Fast Food							
0 - 10	20.3 (607)	17.0 (509)	18.7 (559)	20.0 (598)	24.1 (721)	100 (2994)	1.19
11 - 20	16.2 (132)	19.2 (156)	22.0 (179)	23.5 (191)	19.2 (156)	100 (814)	1.19
21+	13.9 (39)	28.5 (80)	24.9 (70)	21.4 (60)	11.4 (32)	100 (281)	0.82
Takeaway							
0 - 20	21.1 (539)	18.0 (460)	19.0 (484)	18.3 (467)	23.6 (601)	100 (2551)	1.12
21 - 40	14.9 (116)	14.0 (109)	19.8 (155)	27.4 (214)	23.9 (187)	100 (781)	1.60
41+	16.2 (123)	23.2 (176)	22.3 (169)	22.2 (168)	16.0 (121)	100 (757)	0.99
Dairy/Convenience							
0 - 10	24.3 (410)	19.4 (327)	18.7 (315)	16.6 (280)	21.0 (354)	100 (1686)	0.86
11 - 20	15.6 (193)	16.2 (201)	20.5 (254)	22.1 (274)	25.6 (317)	100 (1239)	1.64
21+	15.0 (175)	18.6 (217)	20.5 (239)	25.3 (295)	20.4 (238)	100 (1164)	1.36
Supermarket							
0 - 5	20.6 (638)	17.5 (541)	19.0 (588)	19.4 (602)	23.6 (731)	100 (3100)	1.15
6+	14.2 (140)	20.6 (204)	22.2 (220)	25.0 (247)	18.0 (178)	100 (989)	1.27
Fruit/Vegetable							
0 - 5	19.3 (767)	18.4 (731)	19.9 (792)	20.4 (811)	22.1 (881)	100 (3982)	1.15
6+	10.3 (11)	13.1 (14)	15.0 (16)	35.5 (38)	26.2 (28)	100 (107)	2.54
Activity Facilities							
0 - 10	19.9 (463)	17.5 (407)	18.5 (430)	19.1 (444)	25.1 (584)	100 (2328)	1.26
11 - 20	18.1 (225)	16.8 (208)	20.2 (251)	24.0 (297)	20.9 (259)	100 (1240)	1.15
21+	17.3 (90)	25.0 (130)	24.4 (127)	20.7 (108)	12.7 (66)	100 (521)	0.73

Table shows the proportion and count (in parentheses) of Data Zone with 0-10, 11-20 etc. exposures within 3000 metres (Euclidean-based measure) of the population-weighted centroid, stratified by deprivation quintile

Results from the 800 metre Network-based buffer show that fast food holds a similar relationship to that seen in the 800 metre Euclidean-based buffer (Table 4.6). Takeaway and dairy/convenience also reflect a similar pattern to the 800 metre Euclidean-based buffer demonstrating an exponential increase (Table 4.6). Supermarket and fruit/vegetable again reflect results from the 800 metre Euclidean buffer (Table 4.6). Results for activity facilities, as with the 800 metre Euclidean-based buffer, are fairly mixed.

Table 4.6: *Deprivation and exposures within an 800m Network buffer*

	Deprivation Quintile						
No. of outlets	Q1 Lower	Q2	Q3	Q4	Q5 Higher	Total	Ratio Q5:Q1
Fast Food							
0	21.0 (708)	18.0 (608)	19.0 (642)	19.5 (656)	22.5 (758)	100 (3372)	1.07
1	13.3 (53)	18.0 (72)	23.1 (92)	25.8 (103)	19.8 (79)	100 (399)	1.49
2	2.5 (3)	18.9 (23)	23.0 (28)	28.7 (35)	27.0 (33)	100 (122)	10.80
3+	7.1 (14)	21.4 (42)	23.5 (46)	28.1 (55)	19.9 (39)	100 (196)	2.80
Takeaway							
0	24.2 (599)	19.5 (483)	17.7 (439)	17.0 (421)	21.5 (533)	100 (2475)	0.89
1	14.1 (100)	16.3 (116)	23.1 (164)	23.5 (167)	23.0 (163)	100 (710)	1.63
2	10.6 (34)	14.0 (45)	20.5 (66)	28.6 (92)	26.4 (85)	100 (322)	2.49
3+	7.7 (45)	17.4 (101)	23.9 (139)	29.0 (169)	22.0 (128)	100 (582)	2.86
Dairy/Convenience							
0	24.9 (593)	19.8 (472)	18.4 (439)	17.1 (407)	19.8 (473)	100 (2384)	0.80
1	13.7 (117)	16.0 (136)	22.2 (189)	22.2 (189)	25.9 (220)	100 (851)	1.89
2	11.0 (43)	15.1 (59)	21.7 (85)	29.6 (116)	22.7 (89)	100 (392)	2.06
3+	5.4 (25)	16.9 (78)	20.6 (95)	29.7 (137)	27.5 (127)	100 (462)	5.09
Supermarket							
0	20.5 (701)	17.8 (609)	19.5 (667)	20.1 (687)	22.1 (756)	100 (3420)	1.08
1	12.2 (71)	20.9 (122)	21.4 (125)	23.0 (134)	22.5 (131)	100 (583)	1.84
2+	7.0 (6)	16.3 (14)	18.6 (16)	32.6 (28)	25.6 (22)	100 (86)	3.66
Fruit/Vegetable							
0	19.9 (769)	18.4 (712)	19.5 (753)	20.3 (784)	21.8 (843)	100 (3861)	1.10
1+	3.9 (9)	14.5 (33)	24.1 (55)	28.5 (65)	28.9 (66)	100 (228)	7.41
Activity Facilities							
0	20.1 (616)	17.5 (536)	19.2 (588)	20.1 (615)	23.0 (703)	100 (3058)	1.14
1	17.4 (121)	19.6 (136)	19.6 (136)	21.9 (152)	21.6 (150)	100 (695)	1.24
2	15.2 (32)	18.6 (39)	23.3 (49)	26.2 (55)	16.7 (35)	100 (210)	1.10
3+	7.1 (9)	27.0 (34)	27.8 (35)	21.4 (27)	16.7 (21)	100 (126)	2.35

Table shows the proportion and count (in parentheses) of Data Zone with 1, 2, 3 etc. exposures within 800 metres (Network-based measure) of the population-weighted centroid, stratified by deprivation quintile

Results from the 1600 metre Network-based buffer reflect a similar pattern to the Euclidean-based for dairy/convenience and supermarket categories, where highly deprived areas are slightly less likely to have fewer outlets and more likely to have higher numbers of outlets compared to less deprived areas (Table 4.7). The fruit/vegetable category reflects a similar pattern to the 1600 metre Euclidean-based buffer, however, the proportion of highly deprived areas with two or more fruit/vegetable stores is vastly more than the least deprived areas (Table 4.7). While reflecting a similar pattern to the Euclidean-based buffer, results from the 1600 metre Network buffer showed a stronger social gradient in this category. The takeaway category reflected a similar pattern to that of the Euclidean-based buffer, where areas with fewer outlets are relatively similar, but areas with higher numbers of outlets are more prevalent in highly deprived areas (Table 4.7). Results for activity facilities differ from the 1600 metre Euclidean-based buffer, which demonstrated a declining ratio as numbers of facilities increased, something that is not reflected in the Network-based measure (Table 4.7).

Table 4.7: *Deprivation and exposures within a 1600m Network buffer*

	Deprivation Quintile						
No. of outlets	Q1 Lower	Q2	Q3	Q4	Q5 Higher	Total	Ratio Q5:Q1
Fast Food							
0 - 5	19.8 (748)	18.0 (680)	19.6 (739)	20.3 (766)	22.3 (840)	100 (3773)	1.13
6+	9.5 (30)	20.6 (65)	21.8 (69)	26.3 (83)	21.8 (69)	100 (316)	2.29
Takeaway							
0 - 5	22.5 (680)	18.6 (564)	18.5 (560)	18.0 (546)	22.4 (677)	100 (3027)	1.00
6 - 10	10.4 (62)	16.0 (96)	22.4 (134)	27.9 (167)	23.4 (140)	100 (599)	2.25
11+	7.8 (36)	18.4 (85)	24.6 (114)	29.4 (136)	19.9 (92)	100 (463)	2.55
Dairy/Convenience							
0 - 5	21.9 (716)	18.8 (614)	19.3 (631)	18.5 (604)	21.5 (704)	100 (3269)	0.98
6+	7.6 (62)	16.0 (131)	21.6 (177)	29.9 (245)	25.0 (205)	100 (820)	3.29
Supermarket							
0	23.2 (458)	19.3 (380)	18.4 (363)	17.6 (347)	21.5 (423)	100 (1971)	0.93
1	16.7 (238)	18.1 (258)	20.5 (291)	22.9 (325)	21.8 (310)	100 (1422)	1.31
2	12.2 (58)	14.3 (68)	22.7 (108)	25.9 (123)	24.8 (118)	100 (475)	2.03
3+	10.9 (24)	17.6 (39)	20.8 (46)	24.4 (54)	26.2 (58)	100 (221)	2.40

Table 4.7: Deprivation and exposures within a 1600m Network buffer … continued							
Fruit/Vegetable							
0	21.3 (687)	19 (614)	19.2 (620)	19.4 (626)	21.2 (685)	100 (3232)	1.00
1	12.2 (82)	14.2 (95)	23.4 (157)	24.9 (167)	25.3 (170)	100 (671)	2.07
2+	4.8 (9)	19.4 (36)	16.7 (31)	30.1 (56)	29.0 (54)	100 (186)	6.04
Activity Facilities							
0 - 5	19.7 (755)	17.6 (672)	19.2 (736)	20.7 (793)	22.8 (872)	100 (3828)	1.16
6+	8.8 (23)	28.0 (73)	27.6 (72)	21.5 (56)	14.2 (37)	100 (261)	1.61

Table shows the proportion and count (in parentheses) of Data Zone with 1, 2, 3 etc. exposures within 1600 metres (Network-based measure) of the population-weighted centroid, stratified by deprivation quintile

Results from the 3000 metre Network-based buffer largely reflected those of the 3000 metre Euclidean-based buffer for the fast food, takeaway, dairy/convenience and fruit/vegetable categories (Table 4.8). Results from the supermarket category differ, however, as there was a higher proportion of all outlet numbers for more deprived areas. The activity facilities category reflects the 3000 metre Euclidean-based buffer whereby highly deprived areas are more likely to have fewer facilities and less likely to have higher numbers of facilities (Table 4.8). The ratio within the largest number of facilities shows that less than half of highly deprived areas have 21 or more activity facilities compared with areas in the least deprived quintile (Table 4.8). Overall, the Network-based buffers of all sizes reflect similar patterns to those of the Euclidean-based buffers however with some small variations, as noted.

Table 4.8: *Deprivation and exposures within a 3000m Network buffer*

	Deprivation Quintile						
No. of outlets	Q1 Lower	Q2	Q3	Q4	Q5 Higher	Total	Ratio Q5:Q1
Fast Food							
0 - 10	20.1 (724)	17.8 (640)	19.2 (689)	20.0 (721)	22.9 (823)	100 (3597)	1.14
11 - 20	10.4 (42)	18.6 (75)	23.8 (96)	28.0 (113)	19.3 (78)	100 (404)	1.86
21+	13.6 (12)	34.1 (30)	26.1 (23)	17.0 (15)	9.1 (8)	100 (88)	0.67
Takeaway							
0 - 20	21.0 (673)	17.9 (574)	19.0 (609)	18.9 (605)	23.2 (745)	100 (3206)	1.10
21 - 40	10.0 (51)	15.9 (81)	22.7 (116)	30.8 (157)	20.6 (105)	100 (510)	2.06
41+	14.5 (54)	24.1 (90)	22.3 (83)	23.3 (87)	15.8 (59)	100 (373)	1.09

Table 4.8: Deprivation and exposures within a 3000m Network buffer … continued							
Dairy/Convenience							
0 - 10	22.7 (615)	18.2 (494)	19.2 (519)	17.9 (485)	22.0 (595)	100 (2708)	0.97
11 - 20	12.5 (88)	15.5 (109)	20.7 (145)	26.5 (186)	24.8 (174)	100 (702)	1.98
21+	11.0 (75)	20.9 (142)	21.2 (144)	26.2 (178)	20.6 (140)	100 (679)	1.87
Supermarket							
0 - 2	22.2 (538)	19.3 (467)	19.2 (466)	17.9 (434)	21.4 (519)	100 (2424)	0.96
3+	14.4 (240)	16.7 (278)	20.5 (342)	24.9 (415)	23.4 (390)	100 (1665)	1.63
Fruit/Vegetable							
0 - 2	20.1 (735)	18.3 (670)	20.4 (746)	20.0 (732)	21.1 (769)	100 (3652)	1.05
3+	9.8 (43)	17.2 (75)	14.2 (62)	26.8 (117)	32.0 (140)	100 (437)	3.27
Activity Facilities							
0 - 10	19.9 (679)	17.3 (589)	19.0 (647)	19.9 (677)	23.9 (815)	100 (3407)	1.20
11 - 20	15.2 (82)	21.2 (114)	20.3 (109)	27.3 (147)	16.0 (86)	100 (538)	1.05
21+	11.8 (17)	29.2 (42)	36.1 (52)	17.4 (25)	5.6 (8)	100 (144)	0.47

Table shows the proportion and count (in parentheses) of Data Zone with 0-10, 11-20 etc. exposures within 3000 metres (Network-based measure) of the population-weighted centroid, stratified by deprivation quintile

Overall, buffers of 800 metre showed a social gradient in the following exposure categories: fast food, takeaway, dairy/convenience, supermarket, and fruit/vegetable. This is all categories apart from activity facilities, where the results were varied. Relationships were strongest for the takeaway and dairy/convenience categories. The fruit/vegetable category demonstrated the highest ratios for both Euclidean and Network-based buffers, where highly deprived areas were consistently shown to have more fruit/vegetable stores. The only category for 800 metre Euclidean and Network-based buffers which did not have a clear social gradient was that of activity facilities, which showed mixed results. Buffers of 1600 metre and 3000 metre generally reflect results from the 800 metre buffers, however, the 3000 metre buffer demonstrated an inverse social gradient for the activity facilities exposure category. Compared to all other exposures, this was the only category to have an inverse relationship with deprivation, indicating that at the largest buffer size as deprivation increases access to activity facilities decreases. While results from varying Euclidean and Network-based buffers demonstrated small variations and minor differences, the general direction and strength of relationships remained similar. It is, however, important to consider both types of buffers as incorporating travel through the road network may have varying levels of importance based on the geographic properties of each area in consideration.

Finally, results demonstrating the spatial relationship between greenspace and socioeconomic deprivation are shown in Figure 4.3 and Figure 4.4 where 'E' is used to denote Euclidean-based buffers and 'N' used to denote Network-based buffers. There is little differentiation in the average percentage of public greenspace for all accessibility measures (Figure 4.3). In contrast, there is a higher average percentage of private greenspace in the least deprived areas for all measures of spatial accessibility (Figure 4.4). As deprivation increases the average percentage of private greenspace is shown to decrease almost exponentially, with much lower values of private greenspace in highly deprived areas (Figure 4.4).

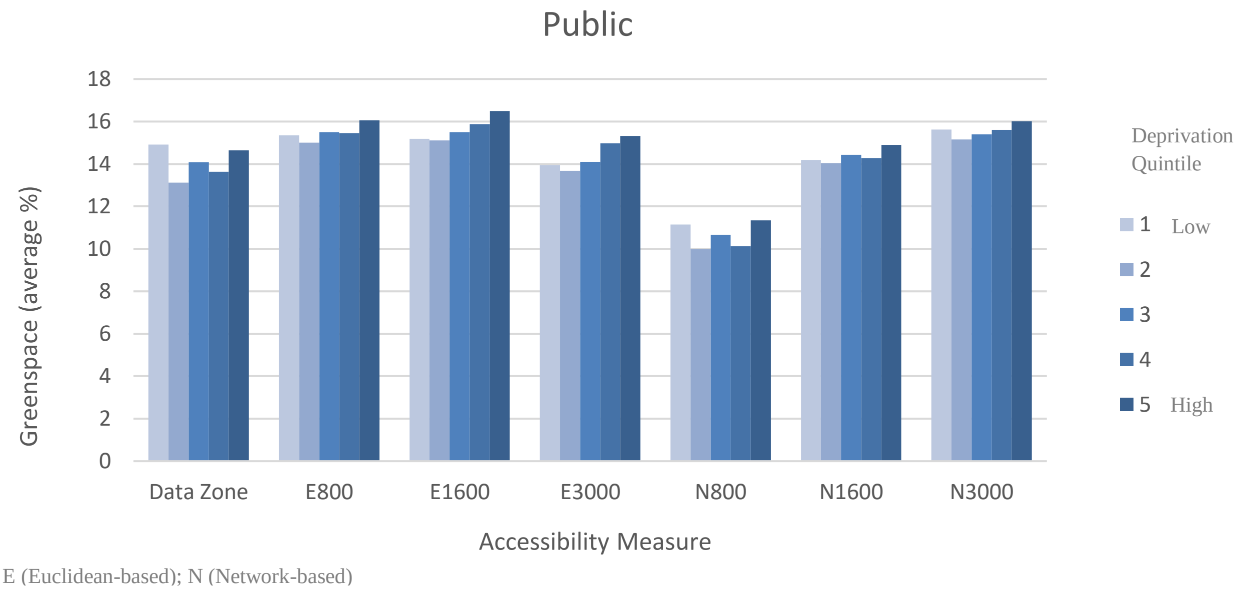

Figure 4.3: *Public greenspace and socioeconomic status by quintile*

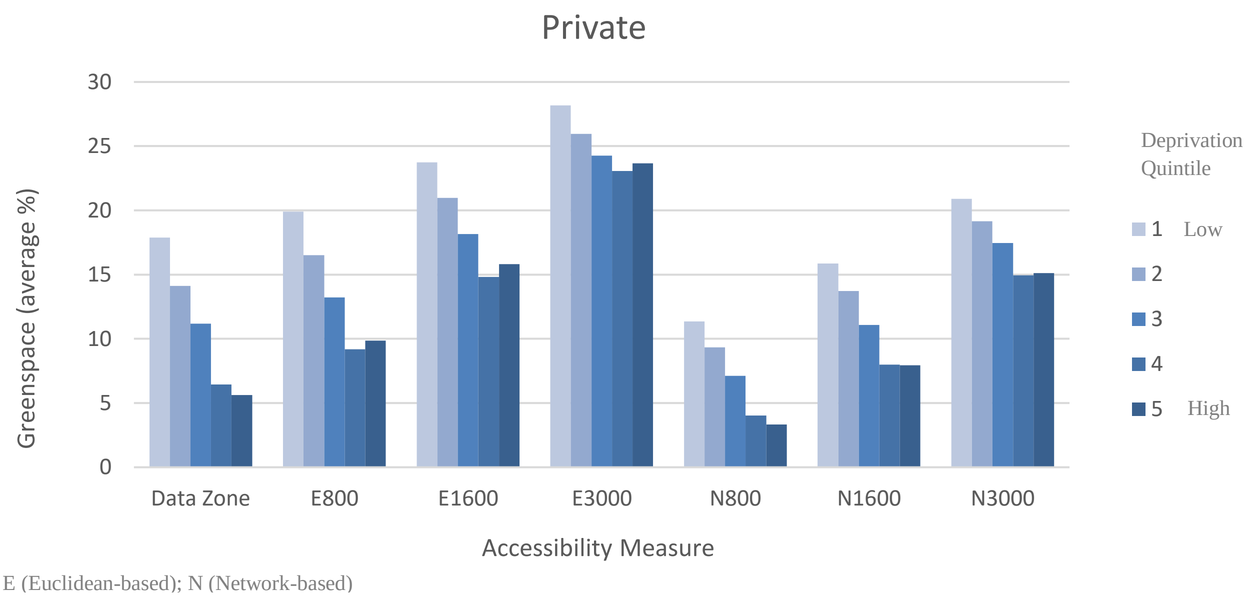

Figure 4.4: *Private greenspace and socioeconomic status by quintile*

Additionally, there are small but significant negative correlations between private greenspace and deprivation at Data Zone scale and for all buffer types and sizes (Table 4.9). This indicates that as deprivation increases areas are slightly less likely to be exposed to private greenspace. Within urban New Zealand this is a common sense interpretation where wealthy areas are likely to have larger property sizes and therefore more private greenspace. If looking at this nationally this may not be the case as a very different pattern may be seen in rural areas. The only spatial measures which showed a significant relationship between public greenspace and deprivation were the 1600 metre and 3000 metre Euclidean-based buffers, although the correlation was very weak (Table 4.9). This indicates less of a relationship between public greenspace and deprivation than between private greenspace and deprivation. Again, this relationship may vary if considering rural areas.

Table 4.9: *Greenspace and deprivation – correlation*

	Data Zone	E800	E1600	E3000	N800	N1600	N3000
Private	-.211**	-.196**	-.153**	-.080**	-.187**	-.177**	-.117**
Public	.002	.028	.061**	.081**	.010	.031	.027

** Correlation is significant at the 0.01 level (2-tailed)

4.4.2 Spatial accessibility: E2SFCA

The average E2SFCA result was highest for takeaway (2.99) and lowest for fruit/vegetable (0.73) (Table 4.10). On the whole this indicates that main urban areas have greater access to unhealthy food environment exposures than to the more healthy food environment exposures of supermarkets and fruit and vegetable stores. Main urban areas also had relatively high access to physical activity facilities. This is expected as there were significantly less supermarket and fruit and vegetable stores within urban areas than the other exposure categories and thus accessibility of these is generally lower. Also, unhealthy food environments and physical activity facilities tend to be clustered in main urban areas to increases sales/patronage.

Table 4.10: *E2SFCA summary*

	Average	Std. Dev		Average	Std. Dev
Fast Food	2.15	1.33	Supermarket	1.56	0.93
Takeaway	2.99	1.34	Fruit/Vegetable	0.73	0.81
Dairy/Convenience	2.95	1.26	Activity Facilities	2.41	1.19

E2SFCA results for Auckland region demonstrate lower spatial accessibility of fruit/vegetable stores as compared to other exposures, with only small pockets of moderate accessibility (Figure 4.5). Supermarkets also tend to be within lower and moderate ranks, however, there are significantly more moderate ranks, particularly in central areas (Figure 4.5). Fast food, takeaway, dairy/convenience and activity facilities reflect similar patterns to each other, where more populated areas show the highest ranks of accessibility (Figure 4.5). Overall, higher accessibility tends to be focused on central areas, which is largely reflective of the processes by which businesses locations are selected.

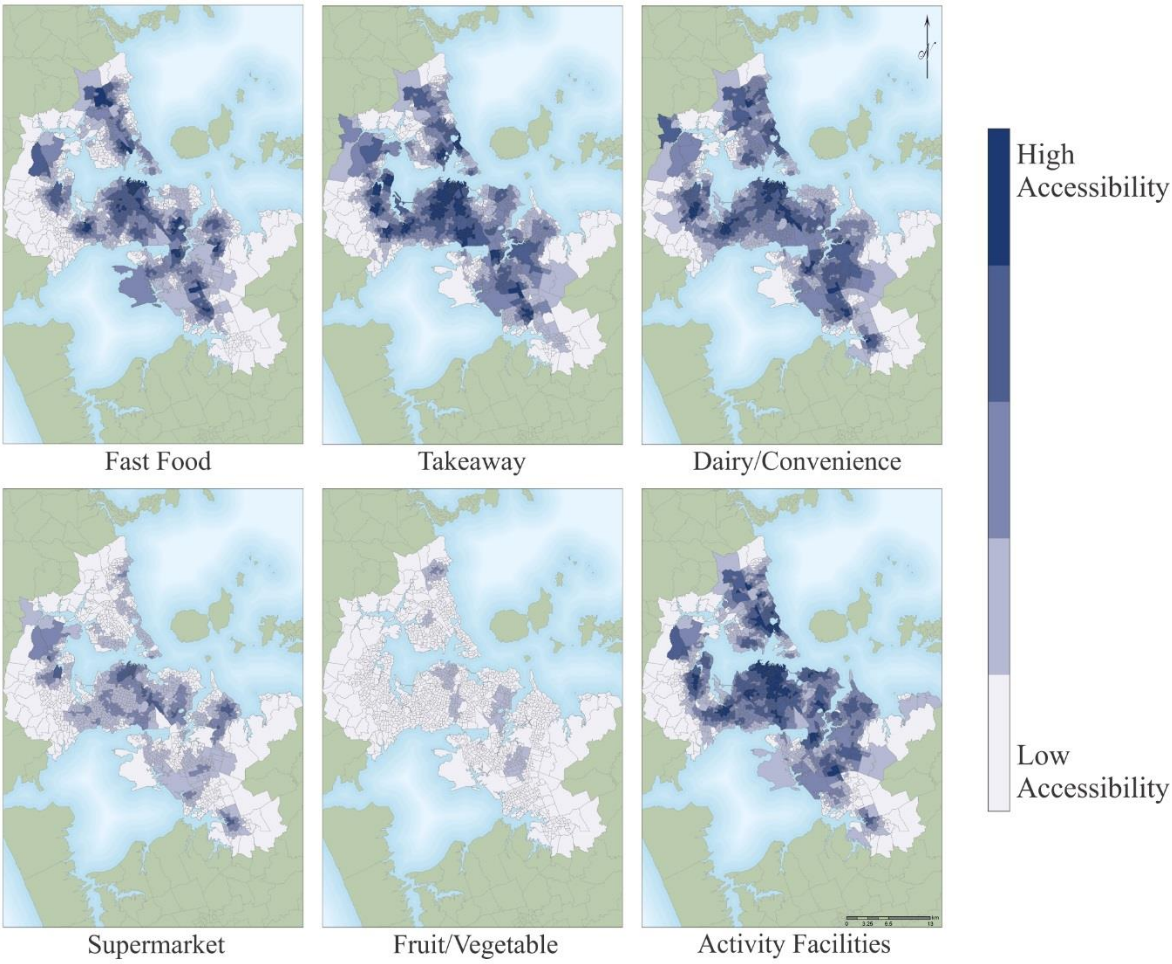

Figure 4.5: *E2SFCA results of spatial accessibility for Auckland region*

Maps of E2SFCA results for Christchurch again reflect the lower spatial accessibility of fruit/vegetable stores and supermarkets compared with other exposures (Figure 4.6). Takeaway and dairy/convenience categories are the most widespread with many areas of high accessibility. Fast food and activity facilities are shown with moderate accessibility with higher areas in the central city, and to the west for fast food (Figure 4.6). For all environmental exposure categories again the areas of highest accessibility are in the central city (Figure 4.6), reflecting a similar pattern to Auckland and again reflective of the processes by which outlets select locations of businesses.

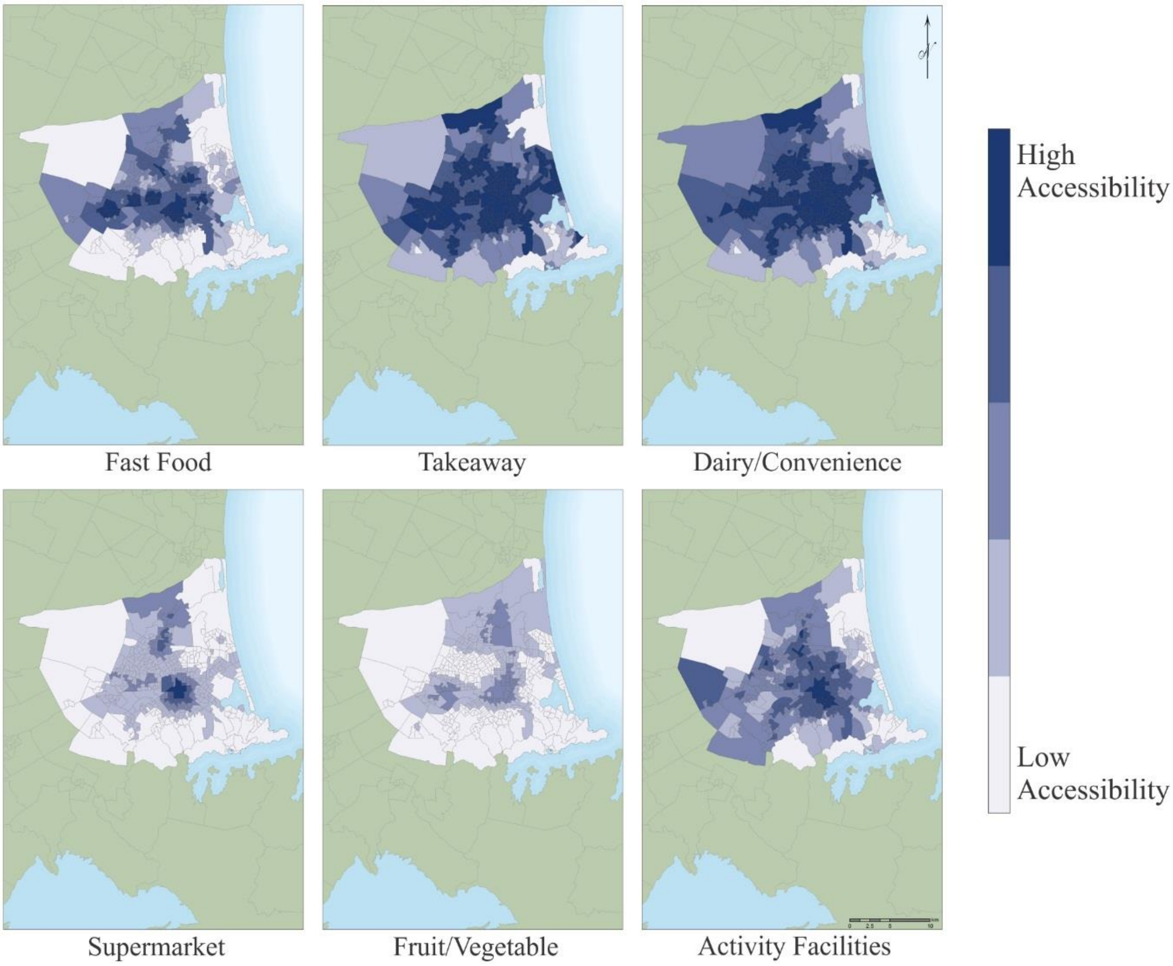

Figure 4.6: *E2SFCA results of spatial accessibility for Christchurch region*

Maps for E2SFCA results for Wellington reflect the aforementioned results, whereby the areas with the highest accessibility are the most central and the most densely populated areas (Figure 4.7). Fruit/vegetable again demonstrates the lowest accessibility, followed by supermarkets which are largely in central areas. There are many pockets of high accessibility for dairy/convenience and takeaway categories, again largely in densely populated and central areas (Figure 4.7). For all exposures, areas outside of the most central and populated areas showed lower spatial accessibility to exposures.

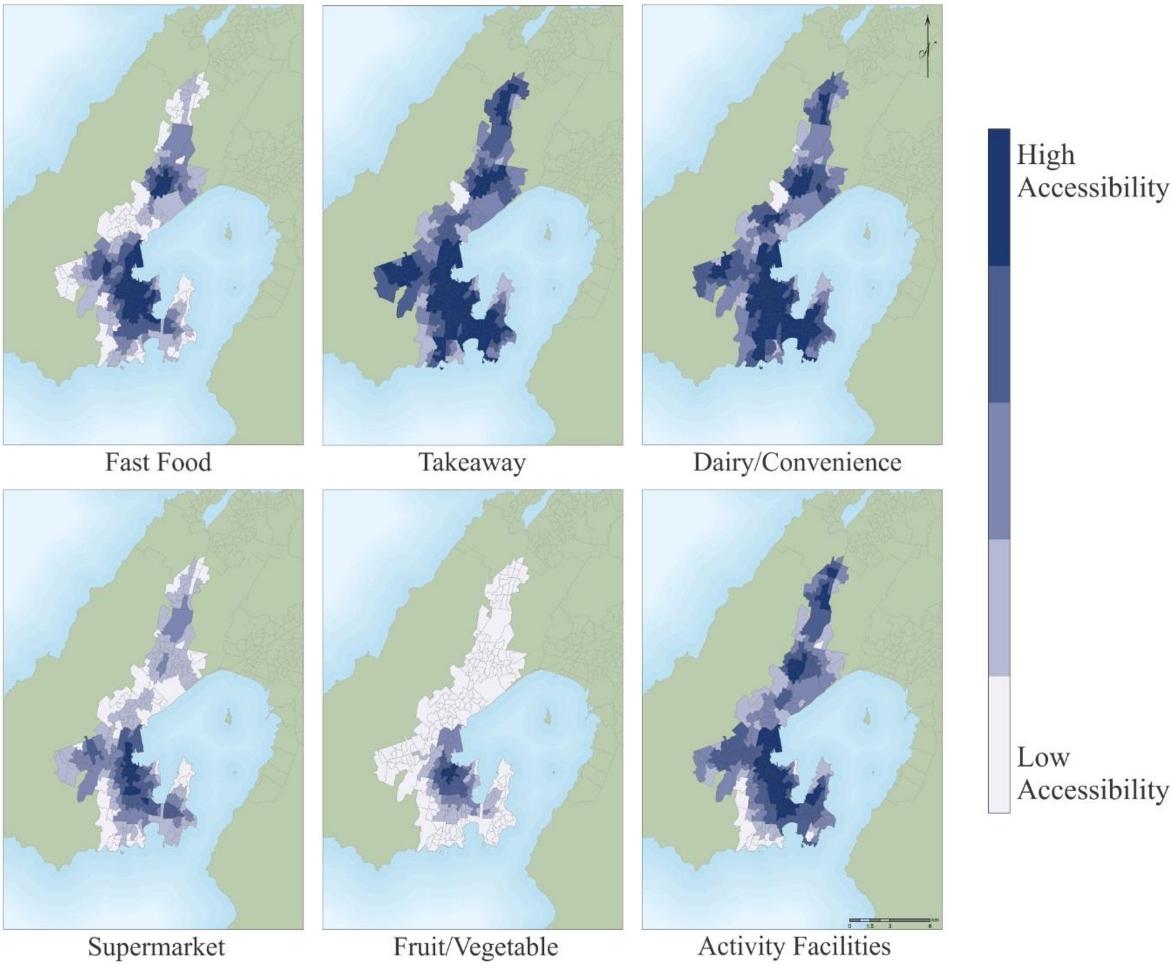

Figure 4.7: *E2SFCA results of spatial accessibility for Wellington region*

This general pattern is reflected in the other main urban areas included in this analysis (Appendix C). The assumption behind such spatial patterns is that areas with the highest accessibility are generally centrally located, densely populated areas where there are more shopping areas and less residential spaces. This is an expected pattern as outlets tend to locate in areas which will provide regular patronage and thus be profitable. While this is often central areas rents can be high in such areas and secondary areas of high accessibility may be less central yet possibly more socially deprived. Generally, urban areas had the highest accessibility to takeaway and dairy/convenience categories, reflecting the higher number of these outlets and the tendency for such outlets to locate in populated areas. Additionally, dairy/convenience is the most widespread category in regard to accessibility, this is likely because such outlets commonly locate throughout residential areas as well as larger central areas and therefore tend to exhibit a less defined spatial pattern. Conversely, fruit/vegetable was the least accessible exposure reflecting both the lower numbers and the relative sparseness of locations.

Results highlighting the relationship between socioeconomic status and the E2SFCA sum weight exposures, given as 0 - 5 to represent lowest to highest accessibility, are given in Table 4.11. Overall, highly deprived areas are less likely to have lower accessibility and more likely to have high accessibility to all environmental exposures apart from activity facilities. The strongest social gradient is seen for the dairy/convenience category whereby highly deprived areas are 64% less likely to have lower accessibility but over three times more likely to have high accessibility (Table 4.11). This was reflected in the fast food, takeaway and supermarket exposure categories, although to a slightly lesser extent. The fruit/vegetable category, while demonstrating that highly deprived areas are roughly five times more likely to have moderate accessibility than less deprived areas, did not show the same pattern in the most accessible measure, which also demonstrated notably smaller numbers (Table 4.11). As discussed previously, this may be due to the very few areas which had the highest accessibility measure to this exposure category, reflecting its sparse nature. Finally, activity facilities was the only exposure category in which highly deprived areas are shown to have a higher ratio than the less deprived area for all ranges of the E2SFCA accessibility measure (Table 4.11), indicating little social gradient.

Table 4.11: *Urban Data Zones – deprivation and E2SFCA exposures*

	Deprivation Quintile						
	Q1 Lower	Q2	Q3	Q4	Q5 Higher	Total	Ratio Q5:Q1
Fast Food							
0 - 1	28.3 (280)	18.0 (178)	17.6 (174)	15.5 (153)	20.5 (203)	100 (988)	0.73
1.1 - 2	22.6 (217)	16.8 (162)	18.4 (177)	19.0 (183)	23.2 (223)	100 (962)	1.03
2.1 - 3	17.6 (162)	19.7 (182)	18.9 (174)	21.1 (195)	22.8 (210)	100 (923)	1.3
3.1 - 4	11.2 (90)	18.6 (149)	23.7 (190)	24.7 (198)	21.7 (174)	100 (801)	1.93
4.1 - 5	7.0 (29)	17.8 (74)	22.4 (93)	28.9 (120)	23.9 (99)	100 (415)	3.41
Takeaway							
0 - 1	31.1 (123)	21.3 (84)	17.5 (69)	13.7 (54)	16.5 (65)	100 (395)	0.53
1.1 - 2	26.3 (173)	17.8 (117)	17.3 (114)	11.1 (73)	27.5 (181)	100 (658)	1.05
2.1 - 3	23.9 (187)	18.3 (143)	19.9 (156)	18.3 (143)	19.7 (154)	100 (783)	0.82
3.1 - 4	17.5 (179)	19.3 (198)	19.2 (197)	21.7 (222)	22.3 (228)	100 (1024)	1.27

Table 4.11: Urban Data Zones – deprivation and E2SFCA exposures … continued							
4.1 - 5	9.4 (116)	16.5 (203)	22.1 (272)	29.0 (357)	22.9 (281)	100 (1229)	2.42
Dairy/Convenience							
0 - 1	34.4 (115)	21.6 (72)	19.8 (66)	12.0 (40)	12.3 (41)	100 (334)	0.36
1.1 - 2	29.5 (191)	17.1 (111)	14.0 (91)	15.9 (103)	23.5 (152)	100 (648)	0.8
2.1 - 3	20.3 (202)	20.1 (200)	21.2 (211)	19.6 (195)	18.6 (185)	100 (993)	0.92
3.1 - 4	17.5 (189)	18.4 (198)	20.2 (218)	19.4 (209)	24.5 (264)	100 (1078)	1.4
4.1 - 5	7.8 (81)	15.8 (164)	21.4 (222)	29.2 (302)	25.8 (267)	100 (1036)	3.3
Supermarket							
0 - 1	27.1 (339)	19.6 (246)	18.6 (233)	15.0 (188)	19.6 (246)	100 (1252)	0.73
1.1 - 2	17.3 (290)	18.1 (304)	18.8 (316)	22.1 (372)	23.7 (398)	100 (1680)	1.37
2.1 - 3	14.2 (114)	15.2 (122)	21.9 (176)	24.8 (199)	23.9 (192)	100 (803)	1.68
3.1 - 4	10.7 (33)	17.9 (55)	23.5 (72)	25.4 (78)	22.5 (69)	100 (307)	2.09
4.1 - 5	4.3 (2)	38.3 (18)	23.4 (11)	25.5 (12)	8.5 (4)	100 (47)	2
Fruit/Vegetable							
0 - 1	22.6 (652)	18.9 (546)	19.3 (559)	18.6 (538)	20.6 (595)	100 (2890)	0.91
1.1 - 2	12.4 (104)	16.3 (137)	22.7 (191)	24.3 (204)	24.4 (205)	100 (841)	1.97
2.1 - 3	6.2 (17)	14.2 (39)	15.3 (42)	32.4 (89)	32.0 (88)	100 (275)	5.18
3.1 - 4	5.8 (4)	20.3 (14)	18.8 (13)	26.1 (18)	29.0 (20)	100 (69)	5
4.1 - 5	7.1 (1)	64.3 (9)	21.4 (3)	0.0 (0)	7.1 (1)	100 (14)	1
Activity Facilities							
0 - 1	24.0 (146)	19.7 (120)	18.6 (113)	13.3 (81)	24.3 (148)	100 (608)	1.01
1.1 - 2	20.5 (193)	17.2 (162)	18.9 (178)	19.0 (179)	24.5 (231)	100 (943)	1.2
2.1 - 3	20.3 (228)	18.0 (202)	17.1 (192)	21.8 (245)	22.7 (255)	100 (1122)	1.12
3.1 - 4	17.0 (174)	16.2 (165)	22.0 (225)	24.4 (249)	20.4 (208)	100 (1021)	1.2
4.1 - 5	9.4 (37)	24.3 (96)	25.3 (100)	24.1 (95)	17.0 (67)	100 (395)	1.81

Table shows the proportion and count (in parentheses) of Data Zone with varying Gaussian-weighted sums of exposures from the population-weighted centroid, stratified by deprivation quintile

4.5 Discussion

Globalisation and urbanisation have led to rapidly changing environments with populations experiencing fundamental shifts in dietary consumption patterns. Food environments are increasingly saturated with energy-dense and nutrient-poor foods with results of this study indicating that highly deprived neighbourhoods have greater access to a range of food providers. This excess of availability, if partnered with the economic accessibility of low-nutrient foods, can impact significantly on population health and could begin to explain patterns of increased negative health outcomes in deprived areas.

This study has demonstrated a social gradient of all food environment exposures, with generally increased spatial accessibility in more deprived areas. Findings support international studies which have found higher densities of environmental exposures, particularly unhealthy exposures, in highly deprived areas (Lamichhane et al., 2013; Macdonald, Cummins & Macintyre, 2007). Interestingly, however, the findings reported here do not support international evidence that food environment exposures commonly considered as healthy tend to be located in less deprived areas (Moore & Diez Roux, 2006; Morland et al., 2002; Walker et al., 2010). Results instead indicate that highly deprived areas are more likely to have both unhealthy and healthy food environment exposures. This is similar to relationships found in previous New Zealand research (Pearce et al., 2007, Pearce et al., 2008a; Pearce et al., 2008b; Sushil et al., 2017) and is reflective of the mixed results found in the United Kingdom and elsewhere. Activity facilities, representing an aspect of the physical activity environment, generally showed mixed results although some measures demonstrated an inverse social gradient whereby highly deprived areas had less spatial access. While this does not align with international research which has demonstrated that activity facilities tend to cluster in deprived areas (Ellaway, Lamb, Ferguson & Ogilvie, 2016; Schneider et al., 2015), it is generally reflective of other international evidence which demonstrates mixed results regarding this aspect of the built environment (Hill et al., 2012; Macintyre et al., 2008). Additionally, greenspace, representing the other aspect of the physical activity environment, also showed mixed results where measures of public greenspace were largely insignificant and measures of private greenspace demonstrated weak relationships with deprivation. This may, in part, be due to the fact that greenspace accessibility was measured objectively. Prior research (Jones, Hillsdon & Coombes, 2009) has argued that perceived accessibility, which also takes into account the quality and safety of greenspace, may be more robust than objective measures alone.

The results of this study expand on prior New Zealand research which demonstrated social stratification in the range and density of environmental exposures in urban areas (Pearce et al., 2008a). This research builds on that of Pearce et al. (2008a) by using not only more up-to-date data, but also a more detailed spatial scale and more nuanced measures of environmental exposures. This research also uses additional environmental exposures, such as fruit/vegetable and activity facilities, which were not used in previous research (Pearce et al., 2008). Furthermore, unlike this study, Pearce et al (2008a) did not distinguish between multinational and local fast food. For this study, this category was divided to into fast food, to represent multinational outlets, and takeaway to represent local outlets. It is also important to note that this study used broader counts of environmental exposures when compared to Pearce et al. (2008a) to ensure that a significant amount of Data Zones were available.

The results of this study for geographic areas, based on Data Zones, are fairly consistent with Pearce et al. (2008a), where all environmental exposures relating to food outlets are significant. Regarding the 800 metre Euclidean buffer, results from this study are broadly consistent with Pearce et al. (2008a) for supermarket and dairy/convenience whereby there is an increasing social gradient. Pearce et al. (2008a) also demonstrate an increasing social gradient for the fast food category, although not an exponential increase, this is reflected in the fast food category of this study but not takeaway which does exhibit a consistently increasing ratio for highly deprived areas. Pearce et al. (2008a) found both a better choice and range of outlets in highly deprived areas, a social gradient which was consistent for all outlet types and not sensitive to the buffer size or type used. The findings of Pearce et al. (2008a) provide evidence that outlets tend to exhibit spatial concurrence, centred in highly deprived areas. While these findings are generally reflected in this study, there were some distinct differences and results were slightly more sensitive to the measure of spatial accessibility used.

While results demonstrated minor differences, the general direction and strength of relationships remained similar despite the measure of spatial accessibility used. This indicates relationships between exposure density and deprivation persist beyond immediate neighbourhoods, stretching into the scope of the wider area. Therefore, even when taking into account accessibility beyond the direct neighbourhood, socioeconomic factors still tend to be associated with exposure to food providers and choice in highly deprived areas. Explanations behind this social patterning are likely reflective of many facets. Notably, the price of land values and zoning measures play an important role in the location of environmental exposures. For example, lower rental costs and restrictions of business locations may encourage businesses to cluster in highly deprived areas. Additionally, public resistance to certain businesses in affluent areas many compound such spatial patterns.

4.6 Chapter summary

In conclusion, this chapter contributes to a growing body of research which assesses contextual understandings of the built environment and socioeconomic deprivation. The purpose of this chapter was to address Objective 2 (see Chapter 1, Section 1.3.1 on ‘aims and objectives’), to create accurate measures of various built environment exposures for comparison with health outcomes. It not only describes the study exposure categories and the various ways in which the built environment was measured but also investigates relationships with socioeconomic deprivation. Previous studies have generally considered isolated environmental exposures or geographic areas and have used limited measures of spatial accessibility such as census area or one buffer size/type. This study has built on this by considering all urban areas of New Zealand and multiple environmental exposures, with various measures of spatial accessibility. In doing, so this chapter has demonstrated social stratification of many environmental exposures, both those considered as healthy and unhealthy, which are disproportionately located in highly deprived areas. Findings reported here highlight the importance of considering multiple environmental exposures and varying measures of spatial accessibility when assessing the built environment. Such findings also contribute to an improved understanding of the contextual relationship between environmental exposures and socioeconomic deprivation in urban New Zealand.

Chapter 5 : A geospatial analysis of the built environment and T2DM in urban New Zealand

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5.1 Preface

Chapter 4 explored various ways of measuring the built environment and investigated relationships between environmental exposures and socioeconomic deprivation. The current chapter is the second of three analytical chapters. It aims to examine the spatial epidemiology of T2DM in urban New Zealand and understand potential associations with the built environment exposures detailed in Chapter 4.

5.2 Introduction

Diabetes is a chronic health condition in which there is a deviation from normal glucose tolerance, primarily because the body's need for insulin is not proportionately matched by the pancreas' ability to produce or regulate it (discussed in detail within Chapter 2, Section 2.2.2). As noted earlier, T2DM is considered to be the most prevalent form of diabetes, with over 90% of people affected having this variation of diabetes (IDF, 2015; WHO, 2015a). Despite a national source of data, the Virtual Diabetes register, there has been little research on T2DM in New Zealand. Notable exceptions are studies by Berkeley and Lunt, 2006; Coppell et al., 2013; Joshy and Simmons, 2006; Sundborn et al., 2007; and Warin et al., 2016. This is particularly true of spatial research, where there is a paucity of research at a national and sub-national level which addresses both prevalence and potential associations with environmental risk factors. Thus, there are two main aims of this chapter. The first is to examine the spatial epidemiology of T2DM in urban New Zealand to better understand spatial patterns and distribution. The second expands on this by analysing the associations between such outcomes and various built environment exposures, as detailed in Chapter 4.

5.3 Methods

5.3.1 Data

Data gained through the use of the national health database and NHI (see Chapter 3, Section 3.4), has been used to develop and monitor nationwide health outcomes. One such area has been the development of a Virtual Diabetes Register (VDR). First implemented in 2005, the

VDR was created to provide annual diabetes estimates in order to inform policy and planning, where there had been little consistent and reliable nationwide data regarding diabetes. The VDR identifies people with suspected diabetes based on their use of healthcare services, linked through their NHI number (Jo & Drury, 2015). To do this, information is collated from the following datasets: 1) hospital discharges coded for diabetes, excluding gestational diabetes, from 1999 onward, 2) outpatient attendance for diabetes and diabetes retinal screening from July 2002 onward, 3) dispensing of pharmaceuticals typically used by people with diabetes within the past two years, and 4) laboratory tests including haemoglobin A1c (HbA1c) and urinary albumin/creatinine ratio (ACR) tests within the past two years (Ministry of Health, 2017b). It is run in March of each year, with each dataset produced as at 31st December of the previous year. Although it has been demonstrated that VDR estimates had a high match rate against primary care records at an aggregate level (Thornley et al., 2011), it is noteworthy that at individual level there may be a number of false positives or negatives. It is also important to note that only some of the information within the VDR comes from diagnostic laboratory data and therefore it may potentially include people incorrectly identified as diabetic. The algorithm used to extract the above information, and subsequently form the VDR, was assessed in 2016 and improvements to this dataset were made in early 2017 (Ministry of Health, 2017b). For this reason this study uses data from the 2016 VDR only, collected using the revised algorithm.

A total of 306,030 records of suspected diabetes cases were supplied for the period 1st January to 31st December 2016 (Figure 5.1). This study's national cohort only includes VDR records where the person was alive at the end of the study period and enrolled in a PHO. The requirement of being enrolled in a PHO aligns with Ministry of Health (2017b) guidelines and was necessary for data quality reasons as the spatial reference, relating to each individual, is drawn from PHO enrolment details. Furthermore, this study's urban cohort, which pertain to the urban Data Zones outlined previously, met the same requirements detailed above. This cohort also had additional requirements including having an urban area spatial reference (meshblock) and complete demographic information regarding age, gender, and ethnicity (Figure 5.1). The focus of this study relates to T2DM (Type 2) which represents approximately 90% of all diabetes cases and has been linked in the literature to numerous environmental exposures through both the food and physical activity environments (IDF, 2015; Li et al., 2010; Stewart et al., 2011; WHO, 2014). In an effort to filter out suspected T1DM records from this study those aged below 30 and treated primarily with insulin were excluded, consistent with prior research (Cox et al. 2007; Harris, 2001). The reasoning behind this exclusion category is that T1DM diabetes generally develops in the early stages of human development and is primarily treated with insulin as the body does not produce it, or enough of it, naturally. From the urban cohort there were a total of 6,124 people below 30 years of age. Of these people 3,871 were also being treated primarily with insulin and were excluded from this study as they were deemed to have T1DM. Therefore, the final Urban Type 2 cohort consisted of 167,272 records (Figure 5.1). These records were aggregated to Data Zone spatial scale and used to represent T2DM prevalence within this study.

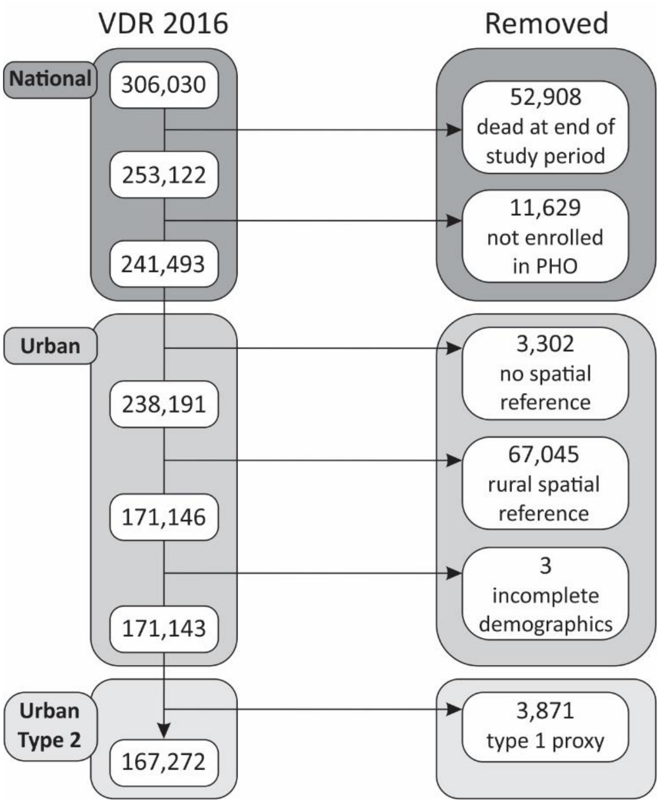

Figure 5.1: *Data eligibility, VDR 2016*

5.3.2 Analysis

Demographic characteristics were analysed at an individual level before the data was spatially aggregated. Once aggregated, analysis can be broadly categorised into the following three areas; data visualisation and mapping, cluster analysis and autocorrelation, and ecological regression. The first two of these categories use an exploratory spatial data analysis (ESDA) approach while the latter uses Bayesian modelling.

A spatial weights matrix was used to assess geographical similarity for all models. The conceptualisation of spatial relationships is therefore an integral component of the spatial analysis conducted, with many different options for measuring area proximity. A neighbourhood spatial weights matrix using the ‘k nearest neighbours’ conceptualisation of spatial relationships, specifying eight neighbours ($k = 8$) for each area, was constructed for this study. The reason for using this method is because urban areas in New Zealand contain both polygons with no contiguous neighbours and clusters of discontiguous polygons (Figure 5.2), which cannot be accurately grouped using contiguity-based methods (ESRI, 2017). Additionally, when data values of spatial areas are not normally distributed it is important to ensure that each area is evaluated within the context of at least eight neighbours. Therefore, the ‘k nearest neighbours’ method specifies that each polygon has eight neighbours, rather than focusing on polygon borders or distance bands. Thus, it is appropriate for use with discontiguous areas as it ensures that all areas are included in the conceptualisation of spatial relationships without having large discrepancies in the number of neighbours.

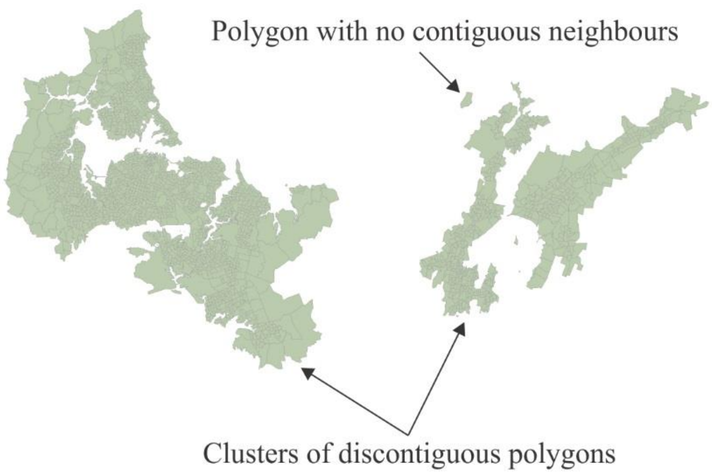

Figure 5.2: *Demonstration of areas with discontiguous or no contiguous polygons*

5.3.2.1 Data visualisation and mapping

The crude rate of T2DM per 1,000 population was calculated for all urban Data Zones and mapped in quantiles. When the population composition of areas differs comparing crude rates can be erroneous as it does not take into account the distribution of the population at risk. Therefore, the age and ethnicity adjusted expected number of cases for each area were calculated using indirect standardisation due to small counts in some population strata and Data Zones. The urban population, sourced from the Census (2013), was used as the standard population for this calculation because it most closely represents the most up-to-date population of interest. Additionally, using this method all urban areas are then comparable to one another. The observed number of cases divided by the expected number, given the standard population, results in a Standardised Morbidity Ratio (SMR). For interpretation purposes, Data Zones with a SMR below 1 have less T2DM cases than would be expected whereas Data Zones with a SMR above 1 have more T2DM cases than would be expected.

5.3.2.2 Cluster analysis and autocorrelation

In this study, Getis Ord General G was used to investigate clustering globally and Getis Ord Gi* used to investigate clustering locally. Global statistics are used to investigate clustering in the most general sense, while local statistics are used to investigate areas in more depth. Such tools effectively analyse where there are hot and cold spots of T2DM, meaning higher or lower than expected clusters, including the value of the area itself in the analysis. Another important aspect that needs consideration when conducting such analysis is spatial autocorrelation which evaluates whether the spatial pattern of values is random, clustered, or dispersed. Moran's I was used to investigate autocorrelation globally, and Anselin Local Moran's I was used to investigate autocorrelation locally. Moran's I statistic is, in essence, a cross-product statistic between a specific variable and its spatial lag, where the variable is expressed in deviations from the mean. The Moran scatterplot, first outlined in Anselin (1996), consists of a plot which has the variable of interest on the x-axis and the spatially lagged variable on the y-axis. Accordingly, the slope of the linear fit given is then equal to Moran's I. As with cluster analysis, global statistics are used to assess autocorrelation in the most general sense, while local statistics are used to investigate areas in more depth. The main difference with autocorrelation is that is does not include the value of the area itself in the analysis, only those of neighbouring features. Neighbours for all analysis were defined using a spatial weights matrix based on the 'k nearest neighbours' ($k = 8$) method, as discussed previously. Importantly, the amount of any disease is generally a function of the population density, for this reason it is most effective to run such analysis on rates or SMR. Therefore, instead of investigating where there are a high T2DM counts such analysis instead investigates where there is an unexpectedly high prevalence given the population size and demographic composition of the area.

5.3.2.3 Ecological regression

Ecological regression analysis was implemented with the aim of identifying and quantifying the effect of environmental exposures on T2DM prevalence. Regression models controlled for age, ethnicity, and deprivation and were run for all spatial accessibility measures using all environmental exposure variables. The dependent variable was age and ethnicity standardised rates of T2DM for each Data Zone and the independent variables were environmental exposures measures and deprivation. The deprivation measure controlled for was the 'IMD no access' measure (Exeter et al., 2017). This utilises the Index of Multiple Deprivation (refer to Chapter 3, Section 3.3), but removes the access component from the deprivation measurement. It was used in this context because of the potential collinearity between this measure and the environmental exposure variables being tested, as they both consider access to similar environmental exposures. First, a non-spatial generalised linear model (GLM) with no random effects was run and the variance inflation factor (VIF) used to detect multicollinearity among predictor variables. There is little consensus on how much emphasis to place on a VIF value, nor which cut-off is most appropriate (Midi & Bagheri, 2010; PVANB, 2016). It has been noted in the literature that this is largely dependent not only on the discipline but also the specific study variables and design however, as a general rule, VIF values in excess of 5 are often considered an indication that multicollinearity is present (Fox & Monette, 1992; Mason, Gunst & Hess, 2003; Midi & Bagheri, 2010; Neter, Kutner, Nachtsheim & Wasserman, 1996; PVANB, 2016). If multicollinearity of independent variables was detected separate regression models were run to ensure accurate results.

Moran's I was used to assess the presence of spatial autocorrelation in the residuals of the GLM models, having the null hypothesis of no spatial autocorrelation. If spatial autocorrelation is present this violates the assumption of independence required by general regression models. The most common remedy for this is an augmentation of the linear predictor, with spatially autocorrelated random effects implemented using Bayesian modelling and represented using a conditional autoregressive (CAR) prior (Lee, 2013). The observed cases in area 'K' are assumed to be of a Poisson distribution with the mean '$p_i E_k$' representing the unknown relative risk and the known expected 'E' number of cases, adjusted for age and ethnicity. Area estimates were then improved by accounting for random effects via spatial smoothing. Inference was conducted in a Bayesian setting using Markov Chain Monte Carlo (MCMC) simulation, via a combination of Gibbs sampling and Metropolis steps, and the 'S.CARbym' model from the CARBayes package version 5.0 in R, version

3.4.3 (Lee, 2017; R Core Team, 2017). The CARBayes package implements spatial generalised linear mixed models (GLMM) for areal unit data and includes models with no random effects in addition to models with random effects, which are modelled by a CAR prior (Lee, 2013; Lee, 2017). The model follows the approach of Besag, York and Mollié (1991) by including both independent and spatially correlated random effects implemented as a CAR model with the following form:

$$\psi_k = \phi_k + \theta_k,$$

$$\phi^k|\phi-^k, W, \tau^2 \sim N$$

$$\phi_k|\phi-_k, W, \tau^2 \sim N\left(\frac{\Sigma_i^K =_1 \omega_{ki}\phi}{\Sigma_i^K =_1 \omega_{ki}} \frac{\tau}{\Sigma_i^K =_1 \omega_{ki}}\right),$$

$$\theta_k \sim N(0, \sigma^2),$$

$$\tau^2, \sigma^2 \sim InverseGamma(a, b)$$

[6]

where the $\theta = (\theta_1 \ldots \theta_k)$ random effects have a mean of zero and a constant variance, and spatial autocorrelation is modelled using φ. For this, the conditional variance is inversely proportional to the number of neighbours and the conditional expectation is the average of the random effects in neighbouring areas. The model is based on 20,000 post burn-in samples and uses a binary specification of the spatial weights matrix ‘*W*’, based on ‘k nearest neighbours’. Gaussian prior means and variances for beta parameters, defaulting to a prior mean of zero (μ_0=0) and a large prior variance (σ20=10^{10}), result in a prior distribution that is almost flat. The default prior specification for (τ^2, σ^2), given as (a = 1, b = 0.01), was used where vague priors reflect a belief that is only weakly held, allowing the observations of the data to be dominant. Additionally, model fitting functions updated the random effects using the Metropolis adjusted Langevin algorithm (MALA) (Roberts and Rosenthal, 1998).

Valid inferences from MCMC samples are based on the assumption that samples are derived from the true posterior distribution of interest and this is generally assessed using convergence diagnostics. Therefore, the Deviance Information Criterion (DIC) was used to assess model fit while trace plots and the Geweke diagnostic were used to assess convergence. DIC is a hierarchical modelling generalisation of the Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC), and is commonly used to assess model fit (Spiegelhalter, Best, Carlin and Van der Linde, 2002). Additionally, Geweke (1992) proposes a convergence diagnostic for single MCMC chains where interpretation is based on

[6] Adapted from Lee (2017). Copyright 2017 by Duncan Lee.

a Z-score. Values that fall inside of the range -1.96 to 1.96 generally indicate acceptance while values outside of this, which fall in the extreme tails of a standard distribution, generally indicate a lack of convergence. The Geweke diagnostic was used, in addition to examining trace plots, to assess model convergence.

5.4 Results

5.4.1 Cohort characteristics

As shown (Table 5.1), there are slightly more males than females with suspected T2DM. The age structure shows a very small number of people aged below 30; this is expected because of the removal of those with suspected T1DM and the fact that T2DM typically occurs in later years of life (IDF, 2015). There are more people in the 30 - 64 age group than aged over 64, which reflects a larger population in this age group in general. The number of people in the over 64 group is relatively high, however, this is again a common occurrence in research on T2DM (IDF, 2015). The ethnicity structure shows much higher numbers for those in the New Zealand European/Other group (Table 5.1), which is expected given that this group comprises the majority of the New Zealand population. When considering other ethnic groups, there are slightly more Pacific Peoples with suspected T2DM than Māori, however, both comprise a significant portion of the sample (Table 5.1).

Table 5.1: *VDR 2016 urban Type 2 sample characteristics*

	N	***%***
Gender		
Female	81,580	48.77
Male	85,692	51.23
Age		
< 30	2,253	1.35
30 – 64	88,915	53.16
> 64	76,104	45.50
Ethnicity		
NZ European/Other	116,415	69.60
Māori	21,672	12.96
Pacific Peoples	29,185	17.45
Total	167,272	100.00

When comparing those living in urban areas with T2DM to the general demographic structure of the country as a whole (StatsNZ, 2013c), they constitute approximately 3.75% of the total female population and 4.15% of the total male population living in urban areas. Regarding ethnicity, they comprise, 9.86% of the total population of Pacific Peoples, 3.62% of the total Māori population, and 3.27% of the total European/Other population living in urban areas. Furthermore, they make up 0.13% of the total population aged below 30 years, 4.62% of the total population aged between 30 and 64, and 12.54% of the total population aged over 64 years living in urban areas. As discussed previously, this age structure reflects the nature of T2DM as a health condition.

5.4.2 Data visualisation and mapping

5.4.2.1 Crude rate

The range of the estimated T2DM population for urban Data Zones was 0.00 – 227.37 per 1,000 population (Figure 5.3). In total 4,083 out of 4,089 urban Data Zones had a diabetic population of 1 or more, and 6 urban Data Zones had no diabetic population. Additionally, for all urban areas the mean rate was 56.61 per 1,000 population with a standard deviation of 27.56. Three urban areas (Cambridge – Te Awamutu, Dunedin, and Upper Hutt) had Data Zones in which there was no diabetic population (Figure 5.3). The mean crude rate was lowest in Wellington at 37.85 and highest in Gisborne, while the standard deviation was smallest in Blenheim and largest in Auckland (Figure 5.3). This indicates that Blenheim has the smallest differences between Data Zone rates while Auckland has the largest.

A Quantile-Quantile (QQ) plot was used to assess normality, or if data values are of a normal distribution. Data values are first ordered and then cumulative distribution values are calculated (as i – 0.5 for the i^{th} ordered value out of a total n values), to give the proportion of data that falls below a given value. A cumulative distribution graph is then created by plotting these values and the ordered data. This same process is repeated for a standard normal distribution and then data values corresponding to specific quantiles are paired and plotted using a QQ plot. Results show that the data are not normally distributed, with particular deviations from normal distribution around the tails (Figure 5.4).

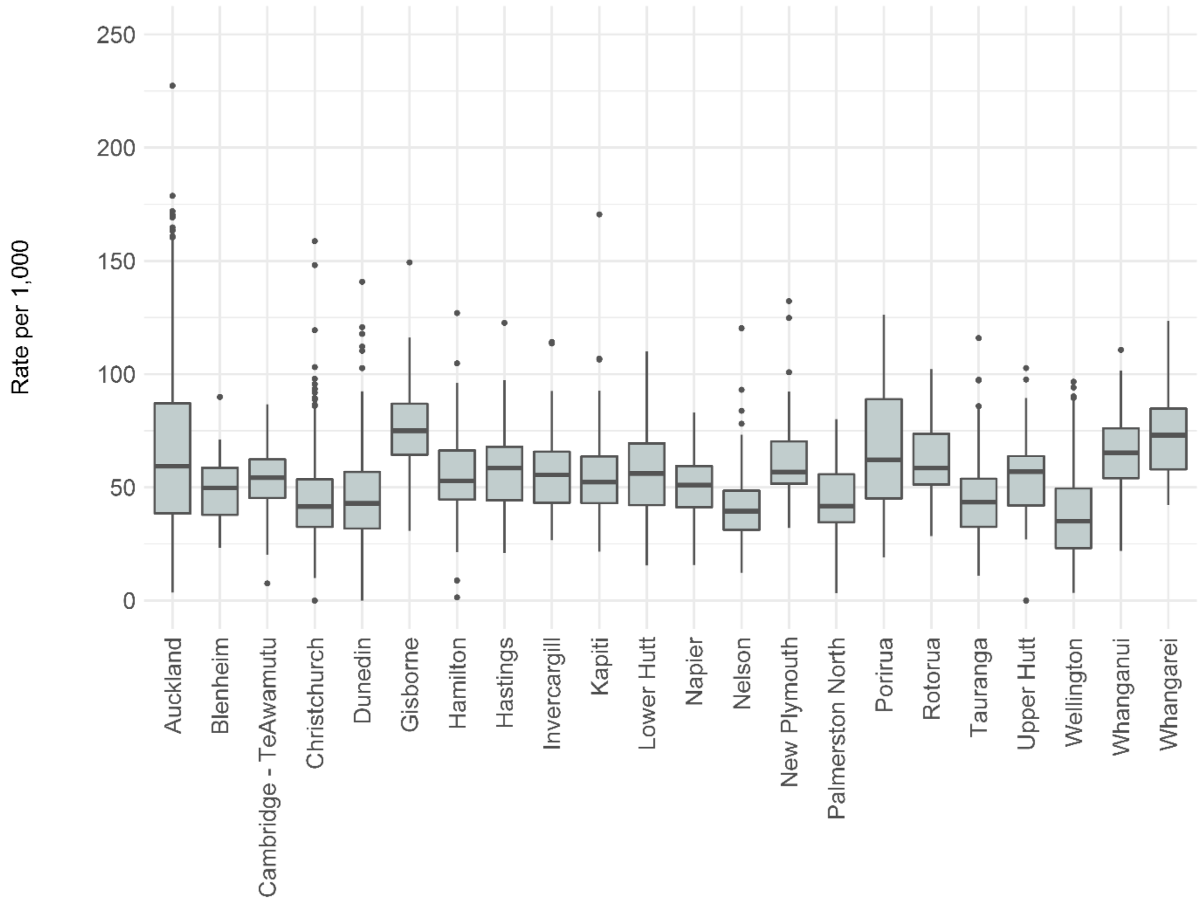

Figure 5.3: *T2DM crude rate per 1,000 for urban areas*

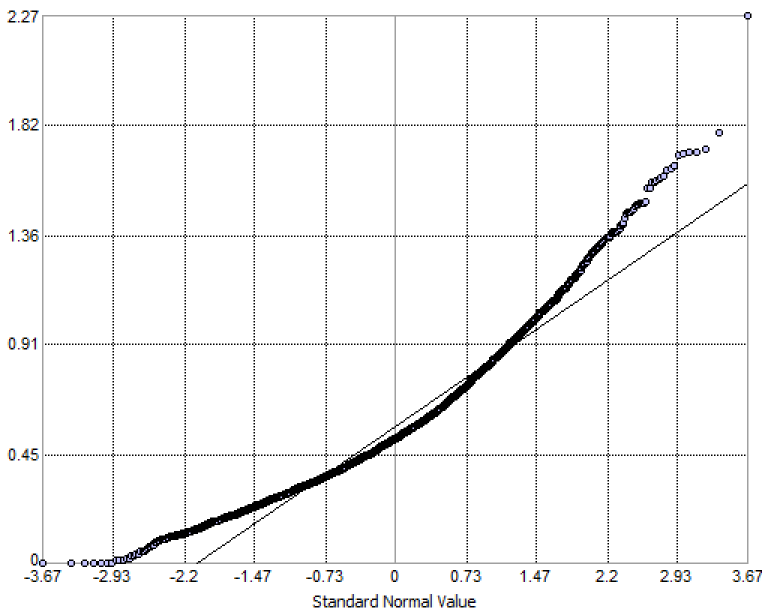

Figure 5.4: *QQ plot of normality for T2DM crude rate per 1,000*

A visualisation of crude rates in Auckland, Wellington, and Christchurch is shown in Figure 5.5, with rates displayed by quartile for all areas to allow for the comparison of maps and avoid having any empty classes. Maps for other urban areas are given in Appendix D. Auckland demonstrates high rates predominately in the south and west, with some pockets of high rates in other areas of the city. Low rates are predominately seen in the central, far east and west, and north of Auckland city (Figure 5.5). Wellington, however, demonstrated pockets of high rates in the south east and pockets of moderate rates in the north east, but low rates elsewhere and overall (Figure 5.5). Additionally, Christchurch demonstrated pockets of high rates in the south west and north east, pockets of moderate rates in the south east and north-west but low rates elsewhere, particularly in the south, central, and north of the city (Figure 5.5). Overall, the rates for Christchurch and Wellington were relatively low with only small areas of high rates which tended to follow a fairly random pattern. Relative to other urban areas, a visual inspection of Auckland showed distinct patterning in the spatial distribution of rates with concentrations of areas with high rates in the south and west and areas of low rates in central, far-east, and northern areas of the city. South and west Auckland demonstrated the most noticeable areas of high rates while central Wellington and southern Christchurch demonstrated the most distinct areas of low rates.

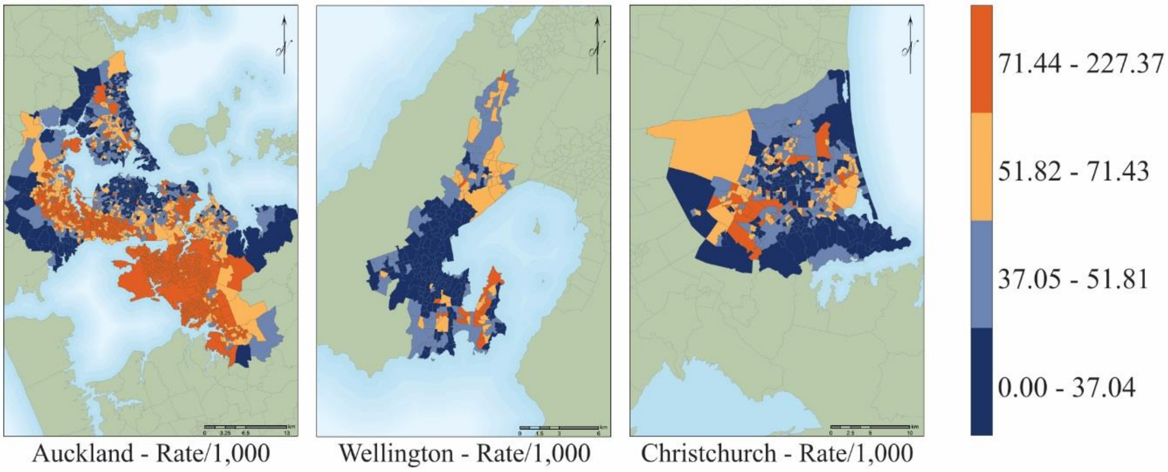

Figure 5.5: *T2DM crude rate per 1,000 population for Auckland, Wellington, and Christchurch*

There were also high rates in Gisborne, Hamilton, New Plymouth, Porirua, Hutt Valley, Rotorua, Whanganui, and Whangarei (Appendix D). Other urban areas with low rates were Blenheim, Dunedin, Te Awamutu, Nelson, and Palmerston North (Appendix D). The area with the lowest rates overall was Blenheim followed by Palmerston North and Nelson. Overall, all other urban areas had a mix of low, moderate, and high rates (Appendix D). The most distinct spatial patterns are those of low rates in Blenheim and southern areas of Palmerston North as well as high rates in northern Hamilton and south/south west Gisborne. Taking into account all urban areas, Auckland demonstrated the most distinct spatial patterning in rates, showing considerable clusters of areas of high rates. This is of interest as it demonstrates this area as one of notable high risk.

5.4.2.2 Standardisation

SMR values ranged from 0 – 5.56, with a mean of 1.02 and a standard deviation of 0.46. The lowest SMR values were in Upper Hutt, Christchurch, and Dunedin, while the highest SMR values were in Auckland. As with the crude rate, Blenheim had the smallest range of values while Auckland had the highest with one extreme outlier (Figure 5.6). This indicates that areas in Blenheim have similar distributions of T2DM while areas in Auckland are more varied and is largely reflective of the amount of Data Zones in these areas. The plot for SMR differs most significantly from that of crude rate for the Gisborne region. This areas is shown to have lower values when controlling for age and ethnicity than when looking at crude rates alone (Figure 5.6).

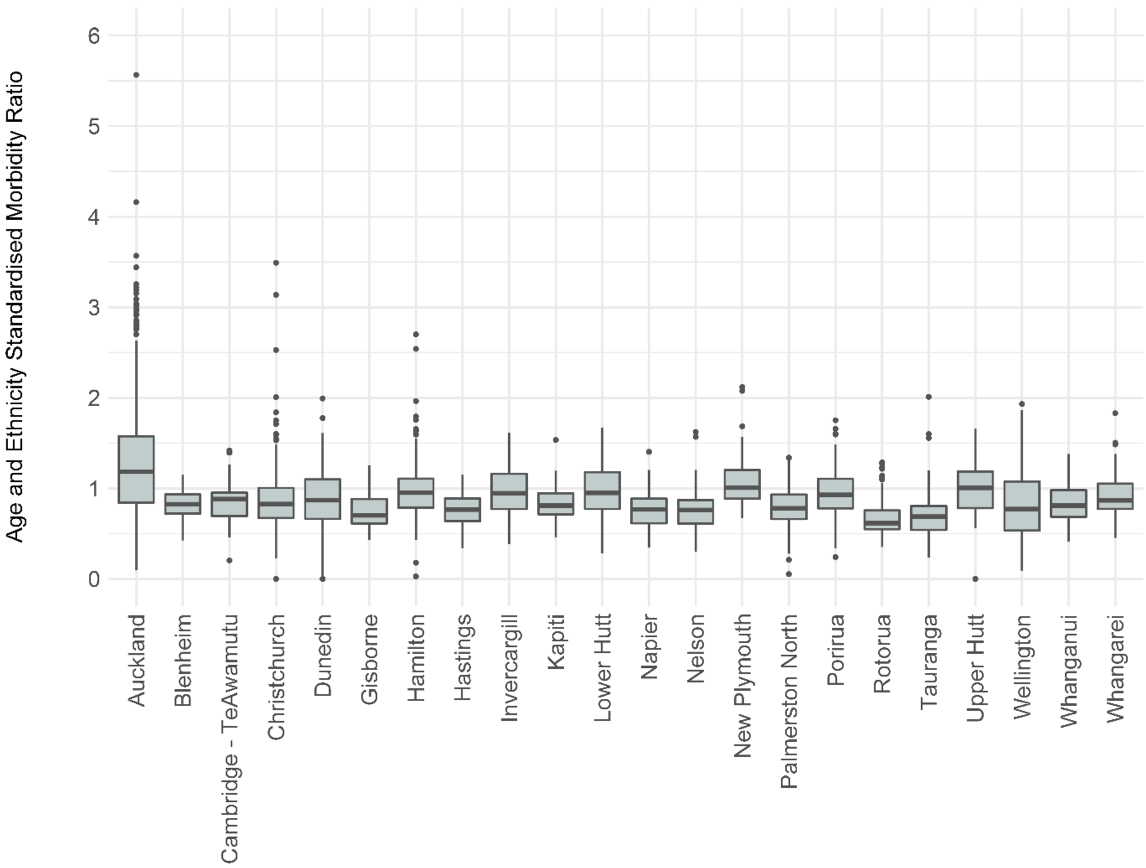

Figure 5.6: *T2DM SMR for urban areas*

When considering SMR the QQ plot again demonstrates that the data are not normally distributed, with deviations from normal distribution around the tails (Figure 5.7).

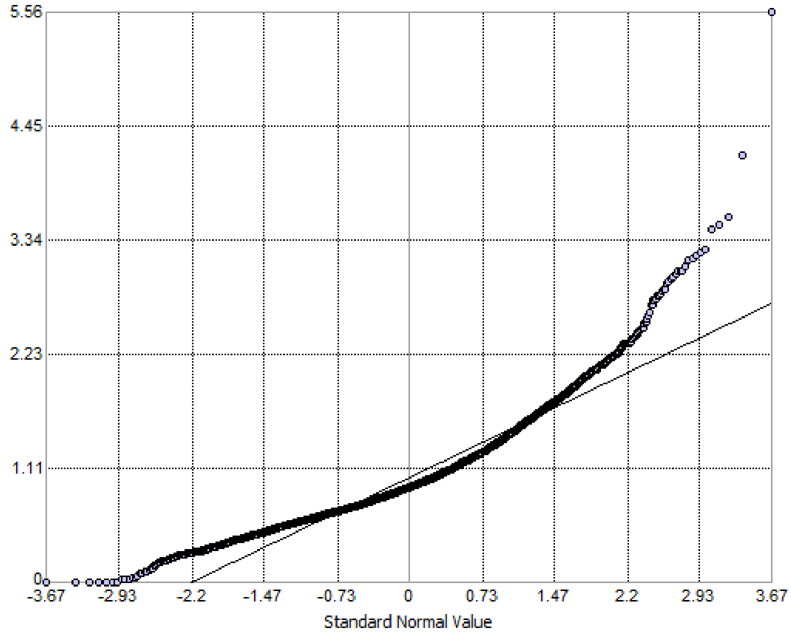

Figure 5.7: *QQ plot of normality for T2DM SMR*

Visualisations of SMR values demonstrate a similar trend as that of crude rate for Auckland with higher values in the south and west and lower values in central, north east, far east and far west of the city (Figure 5.8). As shown, south Auckland in particular has relatively higher SMR values with almost all areas > 1.2, or over 20% higher than expected (Figure 5.8). Regarding Wellington, lower values remain in the central areas of the city with a cluster of areas with SMR values < 0.8 (Figure 5.8). There are areas with higher values in the south east and north, demonstrating similar spatial patterning to that of crude rates. For Christchurch, as with rate, there are clusters of low SMR values in the south and north east of the city. Again, as with rate, there are pockets of high values throughout the eastern and western areas (Figure 5.8). The three main areas of Auckland, Wellington, and Christchurch demonstrate similar spatial patterning for rate and SMR with the most prominent area of high values being southern Auckland.

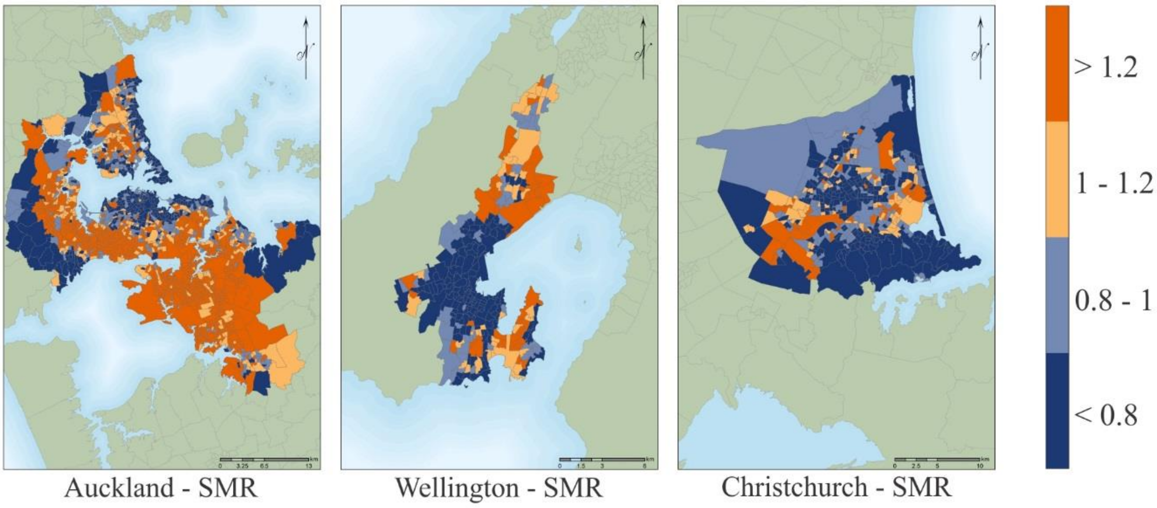

Figure 5.8: *T2DM SMR for Auckland, Wellington, and Christchurch*

For all other urban areas there were low values overall with pockets of high values in most urban areas, although these demonstrated no substantial spatial patterning (Appendix D). Other urban areas with higher SMR values were Hamilton, Cambridge, Porirua, Hutt Valley, and New Plymouth. Other urban areas with the lowest SMR values were Blenheim, Napier, Hastings, Nelson, Palmerston North, Rotorua, Tauranga, and Whanganui. Overall, New Plymouth demonstrated the highest values while Blenheim demonstrated the lowest values (Appendix D). For other urban areas the spatial patterning between crude rate and SMR was similar for: Blenheim, Dunedin, Hamilton, Cambridge, Te Awamutu, Invercargill, Kapiti, Napier, Nelson, New Plymouth, Palmerston North, Porirua, Hutt Valley, and Tauranga. In contrast the spatial patterning between crude rate and SMR was dissimilar for Gisborne, Hastings, Rotorua, Whanganui, and Whangarei (Appendix D). While Gisborne retained an area of high values in the north-west and areas of low values in the north east and south east, the south west of the city shifted from high to low values when considering SMR. Hastings retained similar values in the south, but had lower values in the north than when considering crude rates. Whangarei again maintained a relatively similar pattern to that of rate, but when considering SMR had lower values overall. Rotorua and Whanganui had the most significant differences when looking at SMR (as opposed to rate), whereby the values were significantly lower for SMR than they had been shown for rate alone. Overall, when considering SMR, Auckland showed the most distinct spatial patterning with particularly high values in the south and west of the city. Wellington and Christchurch demonstrated low values overall with pockets of moderate and high values. All other urban areas also demonstrated largely low values with pockets of moderate and high values.

5.4.3 Cluster analysis and autocorrelation

5.4.3.1 Clustering

A pivotal aspect of Exploratory Spatial Data Analysis (EDSA) is assessing spatial clustering to determine if there are areas of high or low clusters in the data. The null hypothesis, and point of reference, for spatial clustering methods is that of spatial randomness, which would suggest that there is no relationship between data values and spatial location. Alternatively, positive values suggest there are clusters of higher values present and negative values suggest there are clusters of lower values present within the dataset. As shown, global clustering results are significant for all measures of T2DM, indicating high clusters (Table 5.2).

Table 5.2: *Global clustering of T2DM*

	General G	Z-score*	*P*-value	Hypothesis
Rate/1,000	0.000286	56.188	<0.001	alternative (high clusters)
SMR	0.000277	48.692	<0.001	alternative (high clusters)

*3 d.p.

Thus, the null hypothesis of spatial randomness may be rejected as the distribution of high values is more spatially clustered than would be expected if the underlying processes were random. Yet, this only indicates the presence of spatial clustering globally and does not provide information on sub-national trends (Holt, 2007). Therefore, in order to determine such information local methods are used, in the form of Getis Ord Gi*.

Results for T2DM crude rate per 1,000 population show hot spots, with 99% confidence, in many urban areas, the most predominant of which are in Auckland and Gisborne (Figure 5.9**,** Appendix D). There are also hot spots, with varying levels of confidence, shown within small pockets of other urban areas (Figure 5.9**,** Appendix D). Overall, the only areas which are clearly defined as having overtly significant hot spots are Auckland (south and west), Gisborne, and Whangarei with a small cluster also in north Kapiti and east Porirua (Figure 5.9**,** Appendix D). Cold spots, with 99% confidence, are also shown in many urban areas and are both more numerous and more spread out in urban areas. Auckland is shown to have cold spots, with 99% confidence, in the central city, north, and far west and east while Wellington and Christchurch demonstrate significant areas of cold spots (Figure 5.9). Tauranga, Palmerston North, Nelson, Napier, Hamilton, and Dunedin also show pockets of cold spots with 99% significance (Appendix D).

There were fewer hot spots when considering SMR. Auckland demonstrated a similar pattern to crude rate whereby areas in the west and south showed clusters of hot spots (Figure 5.9). When considering SMR, far-east Auckland no longer demonstrated cold spots, there were fewer cold spots in the north and additional small pockets of hot spot in the north of Auckland. Generally, however, the pattern was very similar. This similarity in results to crude rate was also shown with Wellington and Christchurch where there remained concentrated areas of cold spots (Figure 5.9). Results are reflective of those for crude rate for the three main areas where Christchurch and Wellington have significant cold spots and small pockets of hot spots and Auckland has significant hot spots with lesser areas of cold spots. The only other areas which showed hot spots for SMR were pockets in Porirua, New Plymouth, Dunedin, and Hamilton (Appendix D).

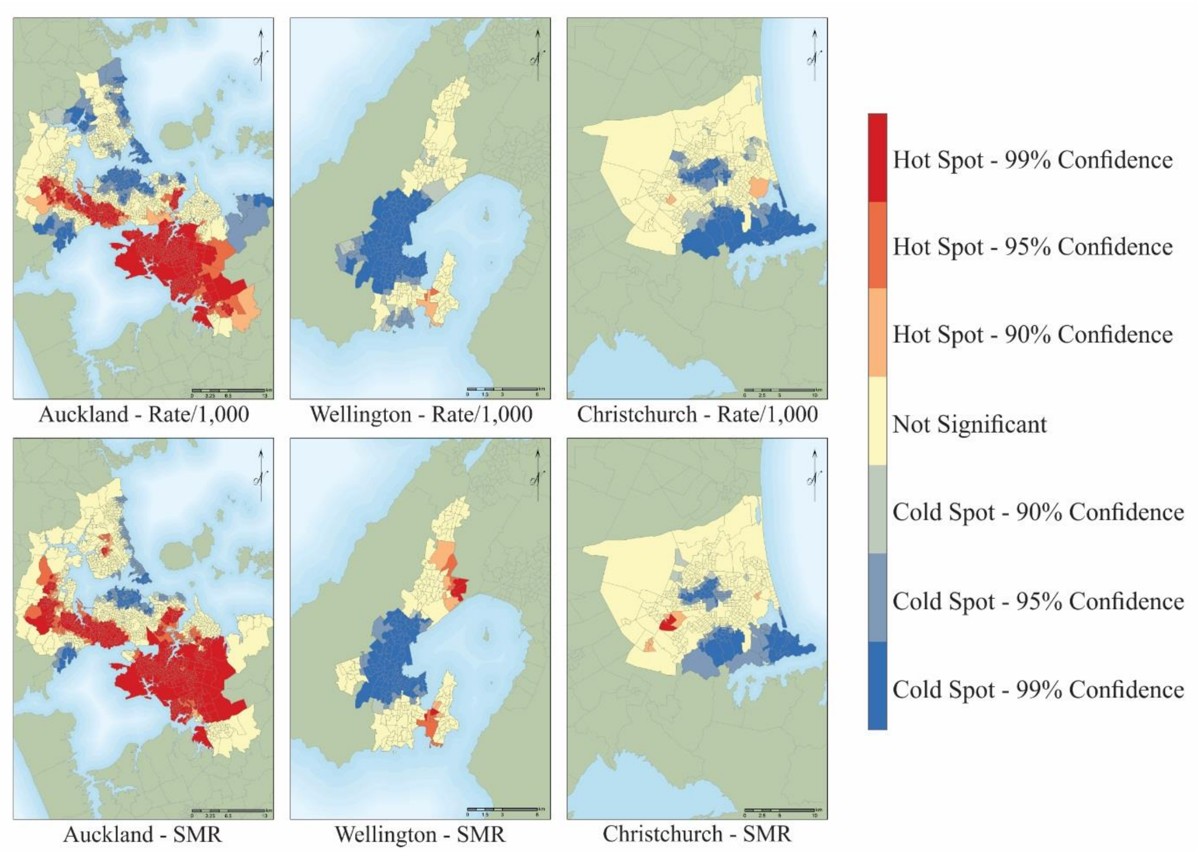

Figure 5.9: *Spatial clustering of T2DM for Auckland, Wellington, and Christchurch*

Overall, cold spots were more frequently observed than hot spots for both T2DM crude rates and SMR. Auckland was the most diverse area in terms of both hot and cold spots of all significance levels. Wellington and Christchurch, while having pockets of hot spots, demonstrated large concentrations of cold spots. Other urban areas showed only pockets of hot and cold spots, the spatial patterning of which was more varied (Appendix D).

5.4.3.2 Autocorrelation

As an uneven spatial distribution of both T2DM crude rates and SMR has been identified across urban areas it is anticipated that the data values of such areas will not be independent of one another. Therefore, it is necessary to test for spatial autocorrelation to determine if the geographical proximity of areas has an influence on the data values. The null hypothesis, and point of reference, for spatial autocorrelation methods is again that of spatial randomness which suggests that there is no relationship between the data values and spatial location. This is assessed using Moran's I which is the correlation between the given variable and its spatial lag and ranges from -1 (strongly dispersed) to +1 (strongly clustered), where 0 is random and indicates no spatial autocorrelation. The Moran's I coefficient is represented by the slope of the linear regression line which runs through the scatterplot. Arguably the most important aspect of this is the classification of the nature of spatial autocorrelation into the following four categories: High-High, Low-Low, High-Low, and Low-High. These are shown respectively by the quadrants of the scatterplot where the upper-right and lower-left quadrants reflect positive spatial autocorrelation, where neighbouring areas have similar values, and the lower-right and upper-left quadrants reflect negative spatial autocorrelation, where neighbouring areas have dissimilar values. As shown, Moran's I statistics are significant and demonstrate evidence that spatial autocorrelation is present in both T2DM crude rates and SMR throughout urban New Zealand (Figure 5.10, Table 5.3).

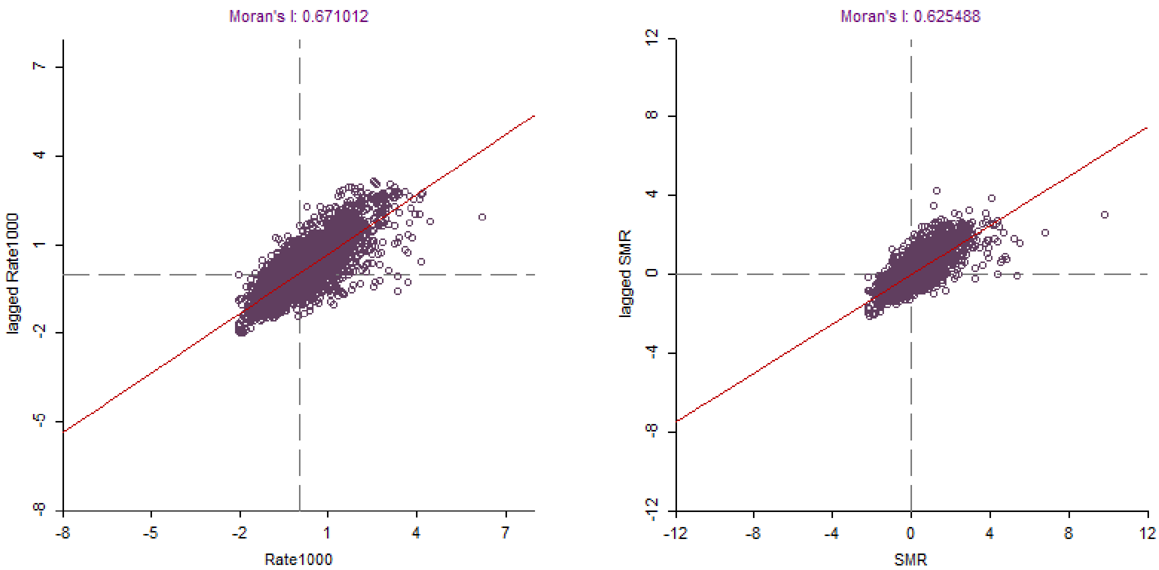

Figure 5.10: *Moran's I scatterplot for T2DM crude rate per 1,000 (left) and SMR (right)*

Table 5.3: *Global autocorrelation – VDR 2016 T2DM*

	Moran's I	Z-score*	*P*-value	Hypothesis
Rate/1,000	0.671132	90.564	<0.001	alternative (clustered)
SMR	0.625594	84.458	<0.001	alternative (clustered)

*3 d.p.

This only indicates the presence of spatial autocorrelation globally, however, and does little to provide further information on the locations of spatial patterns (Holt, 2007). In order to determine whether spatial autocorrelation is present at a sub-national scale local methods, in the form of Anselin's local indicator of spatial association (LISA), is used (Anselin, 1995). Regarding visualisation of local autocorrelation, the cluster/outlier type field distinguishes between a statistically significant cluster of high values (High-High), cluster of low values (Low-Low), outlier in which a high value is surrounded primarily by low values (High-Low), and outlier in which a low value is surrounded primarily by high values (Low-High). This is an important process as it allows the global statistics to be investigated in further depth and identifies particular areas of high risk.

When considering crude rate per 1,000, High-High clusters are shown in Auckland, Whangarei, Whanganui, and Gisborne. There are also small pockets in Rotorua, New Plymouth, Dunedin, Porirua, Hutt Valley, and Kapiti (Figure 5.11**,** Appendix D). Wellington shows no significant High-High clusters and Christchurch shows one small High-High cluster occurs (Figure 5.11). Low-Low clusters are shown in Palmerston North, Nelson, Cambridge, and Dunedin with small pockets also in Tauranga, Hutt Valley, Hamilton, Kapiti, Napier, and Hastings (Appendix D). Low-Low clusters are also shown in Wellington, Christchurch, and Auckland (Figure 5.11). For the latter areas, Low-Low clusters are shown predominantly in central, north, and the far-east and west of Auckland, central areas of Wellington, and central and south east areas of Christchurch (Figure 5.11), with the Low-Low clusters in Wellington and Christchurch more defined than those in Auckland. High-Low outliers are shown in Christchurch and Tauranga with small pockets also in Wellington, Auckland, Hamilton, and Kapiti (Figure 5.11**,** Appendix D). For crude rate, Low-High outliers are shown in Gisborne and Porirua only and did not feature in any of the three main urban areas of Auckland, Wellington, and Christchurch (Figure 5.11**,** Appendix D). Overall, Low-High outliers were the least common followed by High-Low outliers while Low-Low and High-High clusters were more frequently observed. This indicates that it is more common for areas with high or low values to cluster together than to border one another.

When considering local autocorrelation of SMR values, High-High clusters are shown predominately in Auckland (south and west), with small pockets in Wellington, west Christchurch, and north Hamilton (Figure 5.11**,** Appendix D). High-High clusters, when considering SMR, were no longer significant in all other urban areas. When comparing results to those of crude rates, Gisborne no longer demonstrates Low-High outliers but Tauranga remained with some High-Low outliers (Appendix D). Kapiti no longer showed any significance, Porirua and Hutt Valley showed much less significance, and Rotorua showed more Low-Low clusters (Appendix D). High-High clusters remained for the south and west of Auckland, while Low-Low clusters remained for central Auckland. Low-Low clusters also remained for the same areas in which they were shown for rate in both Wellington and Christchurch (Figure 5.11). Wellington, however, is showed small pockets of High-High clusters in the south and north (Figure 5.11). Christchurch retained one of the High-Low outliers shown for rate while the other lost significance. Low-Low clusters were still prominent in central and south east Christchurch and there was a small high-high cluster in the west (Figure 5.11).

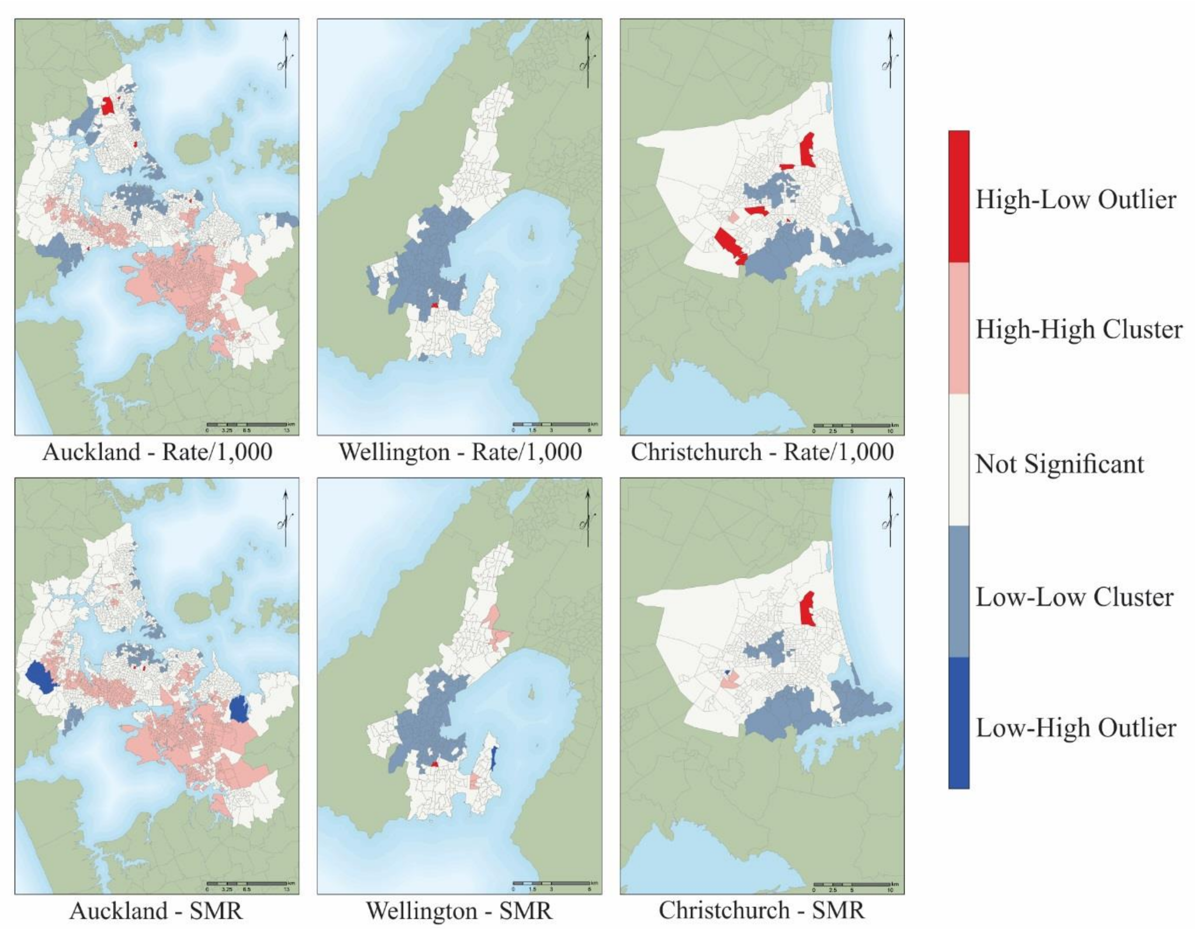

Figure 5.11: *Spatial autocorrelation of T2DM for Auckland, Wellington, and Christchurch*

Overall, Low-Low clusters were the most common throughout all urban areas and only Auckland demonstrated largely significant areas of High-High clusters. Additionally, clusters were more frequently observed than outliers for both crude rates and SMR. This indicates that it is more common for areas with high or low values to cluster together than to border one another

5.4.4 Ecological regression

For ecological regression models, the diabetes data are population level counts of the number of people in each Data Zone with a diagnosis of T2DM. The observed number in each Data Zone are, however, dependent on the size and demographic structure of the population living there. This is adjusted for using indirect standardisation which computes the number which would be expected if national age and ethnicity rates applied. Operationally, this is included in the model as on offset term on the natural log scale. This effectively means that when considering the number of people with suspected T2DM the model takes into account not only the size of the population in each area, but also the age and ethnicity specific demographic structure. All models also account for area-level deprivation.

Additionally, for all models, the continuous rate of environmental exposures led to the best model fit over all other measures tested (tertiles, quartiles, and quintiles), and so were used as the final environmental variable in buffer analysis. For analysis regarding the E2SFCA, environmental exposures were measured on a continuous scale from 0 – 5, as discussed previously (Chapter 4, Section 4.3.2). The greenspace measure was not included for the E2SFCA model as greenspace itself was measured as a percentage within buffers. Because there was no equivalent measure for greenspace using the E2SFCA, however, it is omitted from this model. Furthermore, regression models contained all environmental variables so that given coefficients are conditional on all variables. The only models which exhibited significant multicollinearity, based on a VIF cut-off value of 5, were the 3000 metre buffers where collinearity was detected for the fast food and takeaway categories (Appendix D). Therefore, these variables were fit to separate models as to not affect results. For ease of presentation and interpretation, however, all results are shown in one table. Significant spatial autocorrelation of residuals was present in all ecological non-spatial GLM regression models (Table 5.4). This indicates that the assumption of independence is not withstanding and is common with spatial data in which neighbouring areas tend to have similar values, as evidenced previously.

Table 5.4: *Residual autocorrelation from non-spatial models*

	Moran's I	*P*-value	Hypothesis*
E2SFCA	0.30165	<0.001	alternative
Euclidean 800m	0.30867	<0.001	alternative
Euclidean 1600m	0.29073	<0.001	alternative
Euclidean 3000m	0.31000	<0.001	alternative
Network 800m	0.33330	<0.001	alternative
Network 1600m	0.30313	<0.001	alternative
Network 3000m	0.29750	<0.001	alternative

*Alternative hypothesis is greater for all models (null hypothesis is random pattern)

It is important to take this into consideration when selecting an appropriate regression model to ensure that it is capable of handling spatial data with accuracy. In keeping with this, a Bayesian approach, using a CAR prior, was chosen to model spatial data by adding a set of random effects to the model. Ecological regression models were fitted for the same variables as non-spatial models. Results are presented as median values with 95% Credible Intervals (CI). The CIs indicate a 95% probability that the true parameter is in this range and, on average, it is that given as the median posterior. If the CIs do not include 1 then a parameter within the given range is significant and can be estimated with certainty, as indicated in bold within the following tables. For model fit and Geweke diagnostics refer to Appendix D.

The first spatial regression model examined associations between environmental exposures and T2DM risk using the E2SFCA method of assessing spatial accessibility. It shows a weak but significant positive association between fast food outlet exposure and T2DM risk as well as a significant, but weak, negative association between dairy/convenience, fruit/vegetable, and activity facilities and T2DM risk (Table 5.5). This indicates that areas with higher accessibility of fast food outlets are slightly more likely to have higher T2DM risk whereas areas with higher accessibility of dairy/convenience, fruit/vegetable, and activity facilities demonstrated a protective effect. This was particularly true of fruit/vegetable and activity facilities where a one unit increase in these exposures corresponded to a 6.499% and 5.351% decrease in T2DM risk respectively (Table 5.5). It can be concluded that using the E2SFCA model of exposure accessibility increased T2DM risk is associated, at an ecological level, with increased accessibility of fast food. In contrast, decreased T2DM risk is related to increased accessibility of dairy/convenience, fruit/vegetable, and activity facilities.

Table 5.5: *E2SFCA-based model*

	Median	2.5% CI	97.5% CI
Model 1 – E2SFCA			
Intercept	0.67408	0.62682	0.71648
Fast Food	**1.02337**	**1.00763**	**1.03967**
Takeaway	1.01349	0.99681	1.03097
Dairy/Convenience	**0.97912**	**0.96329**	**0.99501**
Supermarket	1.01106	0.99164	1.03417
Fruit/Vegetable	**0.93501**	**0.91366**	**0.95552**
Activity Facilities	**0.94649**	**0.92969**	**0.96503**

Models 2, 3 and 4 examined associations between environmental exposures and T2DM risk using Euclidean-based buffers of 800m, 1600m, and 3000m respectively as measures of assessing spatial accessibility. Model 2 shows a weak but significant positive association between supermarkets, private greenspace and T2DM risk and a significant but weak negative association between takeaway, fruit/vegetable, activity facilities and T2DM risk (Table 5.6). This indicates that areas with higher accessibility of supermarkets and private greenspace are slightly more likely to have higher T2DM risk whereas areas with higher accessibility of takeaway, fruit/vegetable, and activity facilities demonstrated a protective effect. This was particularly true of fruit/vegetable, where a one unit increase corresponded to a 2.147% decrease in T2DM risk (Table 5.6). In addition, Model 3 shows a weak but significant positive association between fast food, dairy/convenience, supermarket, private greenspace and T2DM risk as well as a significant but weak negative association between takeaway, fruit/vegetable, activity facilities and T2DM risk (Table 5.6). This indicates that, given this measure, areas with higher accessibility of fast food, dairy/convenience, supermarket and private greenspace are slightly more likely to have higher T2DM risk whereas areas with higher accessibility of takeaway, fruit/vegetable and activity facilities demonstrated a protective effect. Model 4 shows a weak but significant positive association between supermarkets, private greenspace and T2DM risk as well as a significant but weak negative association between fast food, takeaway, activity facilities and T2DM risk (Table 5.6). This indicates that areas with higher accessibility of supermarkets and private greenspace are slightly more likely to have higher T2DM risk whereas areas with higher accessibility of fast food, takeaway and activity facilities demonstrated a protective effect.

Table 5.6: *Euclidean-based buffer models*

	Median	2.5% CI	97.5% CI
Model 2 – 800m			
Intercept	0.56984	0.52793	0.61355
Fast Food	0.99900	0.99342	1.00632
Takeaway	**0.99700**	**0.99481**	**0.99910**
Dairy/Convenience	0.99950	0.99521	1.00401
Supermarket	**1.01450**	**1.00170**	**1.02685**
Fruit/Vegetable	**0.97853**	**0.95983**	**0.99710**
Activity Facilities	**0.98030**	**0.97472**	**0.98590**
Greenspace – Private	**1.00220**	**1.00160**	**1.00280**
Greenspace – Public	0.99920	0.99810	1.00030
Model 3 – 1600m			
Intercept	0.54788	0.50743	0.59393
Fast Food	**1.00662**	**1.00270**	**1.01056**
Takeaway	**0.99531**	**0.99392**	**0.99661**
Dairy/Convenience	**1.00301**	**1.00080**	**1.00552**
Supermarket	**1.01939**	**1.01147**	**1.02737**
Fruit/Vegetable	**0.98314**	**0.97258**	**0.99461**
Activity Facilities	**0.98916**	**0.98620**	**0.99203**
Greenspace – Private	**1.00290**	**1.00210**	**1.00361**
Greenspace – Public	1.00010	0.99860	1.00170
Model 4 – 3000m			
Intercept	0.60562	0.56836	0.64908
Fast Food	**0.99283**	**0.99154**	**0.99412**
Takeaway	**0.99740**	**0.99700**	**0.99780**
Dairy/Convenience	1.00050	0.99960	1.00150
Supermarket	**1.01471**	**1.00965**	**1.02000**
Fruit/Vegetable	0.99263	0.98541	1.00060
Activity Facilities	**0.99243**	**0.99094**	**0.99402**
Greenspace – Private	**1.00351**	**1.00260**	**1.00441**
Greenspace – Public	1.00090	0.99860	1.00311

Thus, it can be concluded that using Euclidean-based buffer models of exposure accessibility increased T2DM risk is related, at an ecological level, to increased accessibility of supermarkets and private greenspace. In contrast, decreased T2DM risk is related to increased accessibility of activity facilities and takeaway outlets. This also extended to fruit/vegetable stores for the small and intermediate buffer sizes of 800m (Model 2) and 1600m (Model 3), but not the largest buffer size of 3000m (Model 4).

In addition, Models 5, 6 and 7 examined associations between environmental exposures and T2DM risk using Network-based buffers of 800m, 1600m, and 3000m respectively as measures of assessing spatial accessibility. Model 5 shows a weak but significant positive association between private greenspace and T2DM risk as well as a significant but weak association between takeaway, activity facilities, public greenspace and T2DM risk (Table 5.7). This indicates that areas with higher accessibility of private greenspace are slightly more likely to have higher T2DM risk whereas areas with higher accessibility of takeaway, activity facilities, and public greenspace demonstrated a protective effect on T2DM risk. This was particularly true of activity facilities where a one unit increase in the rate of this exposure corresponded to a 2.303% decrease in T2DM risk. Additionally, Model 6 shows a weak but significant positive association between supermarkets, private greenspace and T2DM risk as well as a significant but weak negative association between takeaway, fruit vegetable, activity facilities, public greenspace and T2DM risk (Table 5.7).

This indicates that areas with higher accessibility of supermarkets and private greenspace are slightly more likely to have higher T2DM risk. In contrast, areas with higher accessibility to takeaway, fruit/vegetable, activity facilities, and public greenspace demonstrated a protective effect. This was particularly true of fruit/vegetable and activity facilities where a one unit increase in the rate of these exposures corresponded to a 2.078% and 1.568% decrease in T2DM risk respectively (Table 5.7). Furthermore, Model 7 shows a weak but significant positive association between supermarkets, private greenspace and T2DM risk as well as a significant but weak negative association between fast food, takeaway, fruit/vegetable, activity facilities, public greenspace and T2DM risk (Table 5.7). As with previous results, this indicates that areas with higher accessibility of supermarkets and private greenspace are slightly more likely to have higher T2DM risk whereas areas with higher accessibility of fast food, takeaway, fruit/vegetable, activity facilities and public greenspace demonstrated a protective effect on T2DM risk. Again, this was particularly true of fruit/vegetable and activity facilities (Table 5.7).

Table 5.7: *Network-based buffer models*

	Median	2.5% CI	97.5% CI
Model 5 – 800m			
Intercept	0.58967	0.55250	0.62475
Fast Food	1.00461	0.99521	1.01430
Takeaway	**0.99571**	**0.99233**	**0.99910**
Dairy/Convenience	0.99342	0.98669	1.00010
Supermarket	1.00401	0.98718	1.02102
Fruit/Vegetable	0.99124	0.96233	1.01969
Activity Facilities	**0.97697**	**0.96793**	**0.98551**
Greenspace – Private	**1.00170**	**1.00110**	**1.00240**
Greenspace – Public	**0.99850**	**0.99750**	**0.99960**
Model 6 – 1600m			
Intercept	0.59744	0.54537	0.65475
Fast Food	1.00160	0.99661	1.00652
Takeaway	**0.99681**	**0.99531**	**0.99850**
Dairy/Convenience	1.00160	0.99820	1.00491
Supermarket	**1.01400**	**1.00441**	**1.02398**
Fruit/Vegetable	**0.97922**	**0.96425**	**0.99432**
Activity Facilities	**0.98432**	**0.98030**	**0.98827**
Greenspace – Private	**1.00180**	**1.00110**	**1.00260**
Greenspace – Public	**0.99820**	**0.99681**	**0.99950**
Model 7 – 3000m			
Intercept	0.60230	0.55527	0.64856
Fast Food	**0.99144**	**0.98965**	**0.99312**
Takeaway	**0.99661**	**0.99621**	**0.99710**
Dairy/Convenience	1.00030	0.99890	1.00180
Supermarket	**1.01979**	**1.01359**	**1.02603**
Fruit/Vegetable	**0.98531**	**0.97609**	**0.99382**
Activity Facilities	**0.98827**	**0.98620**	**0.99025**
Greenspace – Private	**1.00200**	**1.00110**	**1.00290**
Greenspace – Public	**0.99760**	**0.99561**	**0.99960**

Thus, it can be concluded that using Network-based buffer models of exposure accessibility, based on various distances measured through the road network, increased T2DM risk is related, at an ecological level, to increased accessibility of supermarkets and private greenspace. This is reflective of results for Euclidean-based buffers. Decreased T2DM risk, given these models, is related to increased accessibility of activity facilities, fruit/vegetable, public greenspace, and takeaway outlets. Such decreased risk was most notable for the former two exposure categories, however, with very small associations for the latter two categories.

Overall, the takeaway and fast food categories showed very weak results. Although results for the takeaway category were significant for the buffer models, they were not for the E2SFCA model. Additionally, fast food did not show significant results within either of the 800 metre buffer models or the 1600 Network-based model but did, however, show significant effects for other spatial models. The fast food category also demonstrated mixed results, as with the E2SFCA and 1600 Euclidean-based models higher accessibility was positively correlated with relative risk of T2DM while a weak negative association was observed with both the Euclidean and Network 3000m buffer models. Again, relationships were very weak which may contribute to mixed results. The least consistent exposure category was dairy/convenience, which showed very mixed results with significant results for the E2SFCA model and the 1600 metre Euclidean-based model only. Even when considering these two significant results inverse relationships were shown whereby the E2SFCA model showed this category to have a slight protective effect on T2DM risk, but the 1600 Euclidean-based model demonstrated a slightly higher T2DM risk with higher accessibility.

As discussed previously, greenspace was not included in the E2SFCA model and while private greenspace showed significant results for all six spatial buffer models, public greenspace only showed significant results for the Network-based buffers and not for the Euclidean-based buffers. Areas with increased accessibility to private greenspace were shown to consistently have a slightly higher T2DM risk whereas, conversely, areas with higher accessibility to public greenspace were shown to have a slight protective effect on T2DM risk for the Network-based buffers in which they were significant. Again, these results were very weak. In addition, areas with higher accessibility to supermarkets were shown to have a slightly increased T2DM risk but this relationship was not significant for the E2SFCA model or the 800m Network buffer. Furthermore, accessibility to fruit/vegetable stores was shown to have a protective effect on T2DM risk for all models, however, this was not significant for the 3000m Euclidean and 800m Network-based buffers. Activity facilities was the only exposure category to show significant result for all seven spatial models, consistently demonstrating a protective effect on T2DM risk.

To conclude, results demonstrate that fruit/vegetable and activity facilities have not only the most consistent but also the strongest results of all environmental exposures. Additionally, based on the median posterior, the E2SFCA model demonstrated the strongest results of all spatial regression models, particularly for the fruit/vegetable and activity facilities categories. Generally weak results were consistent throughout all buffer models, although some are significant.

5.5 Discussion

When considering demographic patterns the most distinct results were those regarding age and ethnicity. There was distinct patterning of T2DM prevalence with age, with results showing that roughly one in eight adults aged over 64 years have T2DM. This is reflective of the nature of T2DM, a chronic disease which tends to develop in later years of life (IDF, 2015). While generally an expected relationship, this is a notably high proportion of older adults which are affected and raises further concerns about the prevalence of T2DM given New Zealand's ageing population. Additionally, when comparing those with T2DM to the overall demographic structure of populations living in urban areas of New Zealand results demonstrate that there is substantial variation by ethnic group. Both Māori and Pacific Peoples have higher proportions of people with T2DM compared to the European/Other ethnic group. This is particularly true of Pacific Peoples where the proportion of people with T2DM constituted nearly 10% of the population living in urban areas within New Zealand in 2013, three times that of the European/Other ethnic group. While this is high, previous research (Haynes-Maslow & Leone, 2017) has noted that higher T2DM is often witnessed in ethnic minority groups, as discussed in detail earlier (Chapter 2, Section 2.2). This is thought to be largely due to relatively rapid acculturation which has led to significant changes in dietary composition which have not been adequately matched by the body's metabolic pathways (IDF, 2015; Scobie & Samaras, 2014). Regarding demographic results, these are both important findings as they clearly distinguish high risk population groups which may, in turn, help to target and tailor prevention efforts.

As the primary focus of this thesis is on spatial patterning and associations, it is notable that nearly all urban Data Zones had a diabetic population of one or more. Only six Data Zones, out of a total 4,089 (0.15%), had no-one diagnosed as diabetic reinforcing both the high prevalence and widespread distribution of this health issue within urban New Zealand. Results demonstrated that there was significant variation in the crude rate per 1,000 population and SMR of T2DM both within and between urban areas, with the most distinct spatial patterning seen within the Auckland area. Additionally, results of global clustering analysis demonstrated that there were high clusters within both the crude rate per 1,000 and SMR of T2DM. This means that the distribution of values within the dataset is more clustered than would be expected if the underlying spatial processes were random and gives valuable insight into the overall distribution and importance of considering spatial processes. Results of local clustering confirm this, demonstrating notable hot spots within Auckland. The spatial patterning of results for other urban areas, although demonstrating some significance in places, was more varied and less consistent than for the Auckland region. This again demonstrates that Auckland is not only a high risk area but that within the city itself there are distinct regions of particularly high risk, most notably in the south and west. This aligns with previous findings regarding ethnicity and deprivation as these areas of Auckland have notably high populations of Pacific Peoples and are highly deprived, both of which have been shown to increase the risk of T2DM (Sundborn et al., 2007; Warin et al., 2016). Furthermore, when using spatial autocorrelation to determine if the geographical proximity of areas had an influence on the data values, results showed significant positive results for both crude rate per 1,000 and SMR, indicating that neighbouring areas tended to have similar data values. This, in essence, further confirms the spatial patterns shown within cluster analysis. Autocorrelation also revealed that clusters were more frequently observed than outliers, indicating that is it more common for areas with high or low values to cluster together than to border one another. The above provides valuable insight by highlighting the geographic area of greatest risk and providing information on the nature of spatial distribution patterns of T2DM within urban New Zealand.

Results demonstrated autocorrelation of residuals within standard GLM regression models. This again reinforces the importance of considering the spatial nature of the data and substantiates the need for an appropriate regression model which accounts for spatial relationships. Therefore, by using a Bayesian approach to regression analysis such spatial relationships are able to be accounted for. Subsequent results demonstrated some interesting associations, although these were generally weak. Overall, of the exposures considered which would be deemed unhealthy, including fast food, takeaway, and dairy/convenience stores (refer to Chapter 4 for further detail), both the fast food and dairy/convenience categories showed inconsistent results. Interestingly, takeaway outlets often showed a slight protective effect on T2DM risk although this was very weak and cannot be considered substantial. While previous research has demonstrated that fast food outlets, convenience stores, and other unfavourable types of stores and outlets have been associated with negative health outcomes including higher incidence of T2DM (Ahern, Brown & Dukas, 2011; Bodicoat et al., 2015; Gebreab et al., 2017; Mezuk et al., 2016; Turi & Grigsby-Toussaint, 2017), this was not supported by the current results. They do, however, align with other research which has also found little or no association between T2DM and exposures related to such aspects of the food environment (AlHasan & Eberth, 2016; Carroll et al., 2017; Haynes-Maslow & Leone, 2017; Meyer et al., 2015; Morland et al., 2006; Piccolo, Duncan, Pearce & McKinlay, 2015; Stewart et al., 2011). Such variation in results may be reflective of differential zoning regulations and proliferation of these types of exposures within different contexts and/or differing definitions of the exposure itself.

For exposures considered as healthy, including supermarkets, fruit/vegetable stores, greenspace, and activity facilities (refer to Chapter 4 for further detail), many of the results demonstrated fairly consistent significance. Surprisingly, however, the supermarket exposure category demonstrated associations with increased T2DM risk associated with increased accessibility. This is contrary to previous research which has argued that supermarkets are healthy exposures and found opposite associations than the one found within the results of this study (Ahern et al., 2011; Auchincloss et al., 2009; Cunningham et al., 2018; Herrick, Yount & Eyler, 2016). Such research has predominately been conducted within North America, however, which has a relatively distinct spatial patterning of built environment exposures relative to New Zealand. Additionally, given the expansive range of products offered, and the lack of data on food purchasing, the fact that supermarkets offer healthy products does not mean that they are being purchased and subsequently consumed. Supermarkets also offer a substantial range of unhealthy products, particularly pre-packaged foods which are high in refined sugars. Furthermore, the quality of produce such as fruit and vegetables may differ between various supermarkets. This may, in part, contribute to the results seen in this study. Previous research has also shown that increased accessibility to greenspace is associated with a lower T2DM prevalence (Bodicoat et al., 2014; Dalton et al., 2016; Dendup et al., 2018; Lee et al., 2017). It has, however, done little in regard to sub-grouping greenspace into public and private sub-categories so direct comparisons are not possible. It is of interest, however, that private and public greenspace showed opposite relationships with T2DM within the current study whereby the former demonstrated increased risk and the latter a protective effect. While this may be due to many factors, including that public greenspace may be more utilised for physical activity than private greenspace, the associations found were minimal. The most notable protective effect was shown in relation to activity facilities and fruit/vegetable stores however, particularly the former. This aligns with previous research whereby activity facilities and healthy resources have been shown to result in lower insulin resistance and impaired fasting glucose (Auchincloss et al., 2008; Auchincloss et al., 2009; Cunningham et al., 2018). These results concerning associations between exposures of the food and physical activity environments and T2DM are important considerations which both align and conflict with previous research, demonstrating the variability of the New Zealand context.

Much like the current study, a large body of research has also shown mixed or inconclusive results when analysing associations between the built environment and T2DM (see Chapter 2, Section 2.3 and Appendix A.3 for full details). Much of this research (Ahern et al., 2011; AlHasan & Eberth, 2016; Cunningham et al., 2018; Frankenfeld, Leslie & Makara, 2015; Haynes-Maslow & Leone, 2017; Herrick et al., 2016; Lee et al., 2017; Morland et al., 2006; Piccolo et al., 2015; Stewart et al., 2011; Turi & Grigsby-Toussaint, 2017) has, however, been based solely on administrative areas such as census tracts. This does little to measure access beyond arbitrary boundaries and is susceptible to the Modifiable Areal Unit Problem (MAUP) and the Uncertain Geographic Context Problem (UGCoP – see Kwan, 2012), and may therefore misclassify relevant study areas. Other research has sought to address such issues of spatial restriction by constructing buffers, which can be either Euclidean or Network-based, in order to capture a larger study areas which are potentially more relevant. Such research has used many buffer sizes, with the most common including 500 metres (Bodicoat et al., 2015), 800 metres (Dalton et al., 2016), 1000 metres (Mezuk et al., 2016), 1600 metres or roughly a mile (Auchincloss et al., 2008; Auchincloss et al., 2009; Carroll et al., 2017; Christine et al., 2015; Gebreab et al., 2017), and 3 kilometres (Bodicoat et al., 2014; Meyer et al., 2015).

Some research has also sought to remove issues around boundary and edge effects caused by administrative units and buffers altogether by using metrics such as closest distance (Auchincloss et al., 2008). Such measures are often restricted to only considering the one exposure which is closest, however, and can therefore disregard associations with exposures at a further distance which may still be geographically accessible and of importance. To account for these concerns various buffer sizes, as well as the E2SFCA model measuring accessibility to the five closest of each environmental exposure, were used within this study. This provides not only a means of judging associations within different accessibility metrics but also serves as a means of sensitivity analysis to assess how results varied by the accessibility metric used. While the current study did not find vast differences in results between buffers, of both Euclidean and Network design, it did show a difference in results when considering the E2SFCA. The results from this model, although following a similar pattern to those of buffers, demonstrated stronger associations for the exposures deemed significant. This emphasises the importance of including more advanced measures of spatial accessibility beyond administrative units and buffers alone.

Results of this study should, however, be interpreted with consideration of its limitations. Firstly, this study is ecological in nature and may be prone to issues regarding aggregation. Secondly, as this study is cross-sectional it can only provide a limited measure of spatial accessibility over a given time and may also be susceptible to issues of residential self-selection. Additionally, as this study only focuses on urban areas it is unable to capture the spatial epidemiology of T2DM in rural areas. While rural areas were excluded from this analysis due to the uncertainty of reliable data and heterogeneous nature of environmental exposures this is an aspect of T2DM in New Zealand which warrants further investigation.

Furthermore, there are many factors besides spatial proximity that should be taken into account when trying to assess how populations access environmental exposures such as quality of environments as well as the quality and cost of products and services. In fitting with this, food knowledge is another important factor to consider as this is likely to influence purchasing and consumption patterns. Finally, not only do populations regularly access food and areas for physical activity outside of their direct neighbourhood, but their perception of neighbourhood may differ from the measures used in this study. Thus, longitudinal studies and further assessment of the influence of quality, cost, food knowledge, and mobility patterns of residents is needed to fully understand relationships discussed within this study.

5.6 Chapter summary

This chapter contributes to an international body of research which focuses on spatial distributions of T2DM and ecological associations with both the food and physical activity environments. The purpose of this chapter was to address Objectives 3 and 4 (see Chapter 1, Section 1.3.1 on 'aims and objectives'), by investigating the spatial distribution of T2DM in urban New Zealand and examining potential associations with built environment exposures. Previous research has largely focused on the use of administrative areas and buffers as a means of assessing spatial accessibility. This chapter has advanced on this by also considering an alternative measure using an E2SFCA model. Additionally, it has used a national level dataset to assess T2DM prevalence rather than focusing on a specific city or isolated geographic area, thus offering a more comprehensive view of this health issue. In doing so, this chapter has demonstrated distinct demographic and spatial patterning of T2DM as well as some interesting associations with the built environment. While these results do not offer unequivocal proof that particular built environment exposures may cause, or have a protective effect, on T2DM they do demonstrate some significant spatial associations which warrant further attention.

Chapter 6 : A geospatial analysis of the built environment and childhood weight status in urban New Zealand

6.1 Preface

Chapter 5 examined the spatial epidemiology of T2DM in urban New Zealand and explored potential associations with the built environment. Another public health concern in New Zealand is the rate of obesity, particularly among children. This chapter, the third and final analytical chapter, aims to investigate the spatial epidemiology of high weight status in children aged 4 – 5 years within urban New Zealand and understand potential associations with the built environment exposures detailed in Chapter 4.

6.2 Introduction

The focus of this chapter is on weight status in children as national level data was available for this age group. Additionally, high weight status in children is a rising concern which may continue to affect the overall prevalence of overweight and obesity in future years. High weight status is a chronic health issue that research suggests is a risk factor for many adverse health outcomes including T2DM, heart disease, and hypertension among others (Reidpath et al., 2002; WHO, 2014). Maintaining a healthy body weight and adipose level is influenced by the energy balance which accounts for both energy intake and energy expenditure as well as many other factors such as lipostatic set point, metabolic rate, and genetic predisposition (see Chapter 2, Section 2.2.2).

As noted earlier, obesity is a substantial health concern which is estimated to affect more than 40 million children aged 5 and under worldwide (WHO, 2014). It can not only affect mortality, but also quality of life. Within New Zealand, high body weight in children is a significant health concern with an estimated one in every nine children classified as obese (Ministry of Health, 2016b). These figures are even higher when considering high weight status as a whole, including children who are classified as overweight as well as obese. Children of ethnic minorities, such as Māori and Pacific Peoples, and those living in socioeconomically deprived areas are shown to have the highest prevalence (Ministry of Health, 2016b). It is estimated that 30% of Pacific children and 15% of Māori children are obese (Ministry of Health, 2016b). Additionally, children living in the most deprived areas have been shown to be at greater risk of having high weight status and are thought to be five times as likely to be obese when compared to children living in the least deprived areas (Ministry of Health, 2016b). It has been argued that such associations are more pronounced for children than adults, and an estimated 80% of obese children will remain with high weight status into adulthood (Kelly & Swinburn, 2015).

The Before School Check (B4SC), discussed in more detail within Section 6.3.1 below, is a source of national data in New Zealand which provides information on the height and weight of 4 – 5 year old children prior to their enrolment in school. It has been used within previous New Zealand research to analyse trends in weight status (Rajput et al., 2015). There is, however, a dearth of research which focuses on the spatial distribution of high weight status in this age group and potential associations with environmental risk factors. Thus, there are two main aims of the current chapter. The first is to examine the spatial epidemiology of high weight status in 4 – 5 year old children within urban New Zealand in order to better understand spatial patterns and distribution. The second expands on this by analysing the associations between overweight/obesity and various built environment exposures, as detailed in Chapter 4.

6.3 Methods

6.3.1 Data

Data on childhood weight status is from the B4SC, 2013 – 2016. This is a national programme which was launched in 2009 and constitutes the 13th wellness check for children enrolled in the Well Child Tamariki Ora programme (StatsNZ, 2017). It is a cross-yearly survey conducted between July and June of the following year and covers a range of measures which aim to address health, social, behavioural or development concerns in 4 – 5 year old children prior to school attendance. The B4SC is delivered through visits to pre-schools, kindergartens and community-based clinics from health professionals who enter data into a national database managed by the Ministry of Health. Participation is voluntary, however, coverage rates are high and continue to increase with an estimated 90 percent coverage for the first time in 2013/14 (StatsNZ, 2017). This research uses data from three years, 2013/14, 2014/15 and 2015/16.

For anthropometric procedure, duplicate measurements for standing height (to the nearest 0.1 centimetre) and weight (to the nearest 0.1 kilogram) are taken and an average is calculated. Weight is measured without shoes and in light day clothing. Standard weighing scales placed on a hard surface are used for weight measurements and either a Leicester or Seca 214 portable stadiometer are used for height measurements. Height, weight, and Body Mass Index (BMI) of all children in the B4SC (2013 – 2016) were evaluated, using the WHO Child Growth Standards (2006), by comparing a child's body measurement with the expected value of a child of the same age from the WHO reference population. This was done to assess how the weight status of New Zealand children compares to an international standard. WHO (2011) Anthro software version 3.2.2 was used to calculate height and weight z-scores based on the above standards. Children with biologically extreme or implausible values, considered as height or weight z-scores outside of -5 to +5 range, were excluded from all analysis consistent with prior research (Rajput et al., 2015). The 85th and 95th percentiles from the WHO child growth standards (2006) were used as cut-offs for overweight and obesity respectively (Table 6.1), again consistent with prior research (Rajput et al., 2015).

Table 6.1: *WHO child growth standards (2006)*

BMI (kg/m2)	**Classification**
< 5th percentile	Underweight
5th to < 85th percentile	Healthy Weight
85th to < 95th percentile	Overweight
≥ 95th percentile	Obese

A total of 169,573 records were supplied for the period 1st July 2013 to 31st June 2016 (Figure 1). This study's national cohort includes records where the child completed the B4SC within the study period (1st July – 31st June of the relevant year), were within the age range of 4 – 5 years old (48 – 60 months), had complete demographic information (age, gender, and ethnicity), and had plausible anthropometric z-scores (height, weight, and BMI). Furthermore, this study's urban subgroup, which pertain to the urban Data Zones outlined previously, met the same requirements detailed above with the additional requirement of an urban area spatial reference (based on meshblock). All meshblock spatial references were then aggregated to Data Zone spatial scale, forming the basis for spatial analysis within this study. Finally, children from the urban cohort who were deemed to be overweight or obese, as defined by the WHO child growth standards above, were included in this study's urban overweight/obese cohort which represents high weight status as an overall category. This final study subgroup consisted of 20,836 overweight and 18,015 obese children for the years 2013 – 2016 (Figure 1), which were used to calculate crude rates and standardised morbidity ratios. Further details on each of the above detailed cohorts, for each annual time period, can be found in Appendix E.

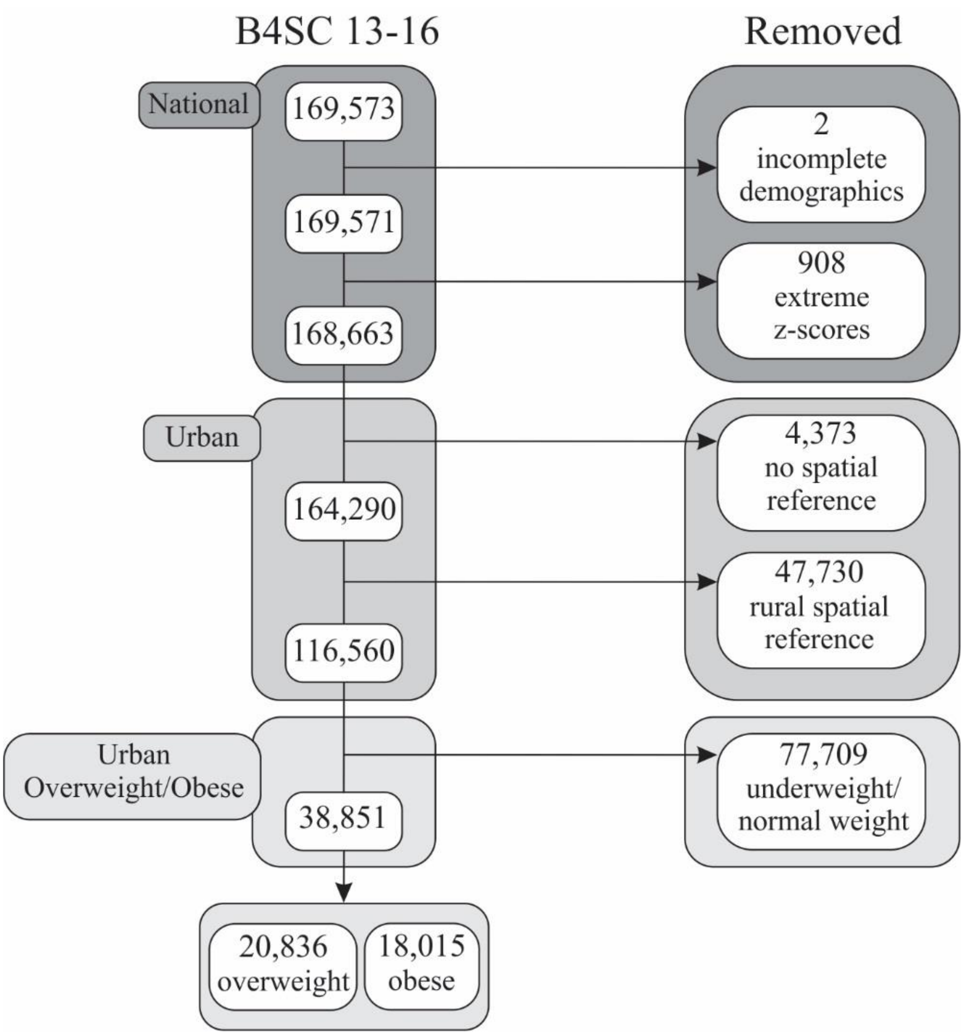

Figure 6.1: *B4SC data eligibility, 2013-16*

6.3.2 Analysis

Demographic characteristics, analysed at an individual level, as well as z-score comparisons and ordered logistic regression were completed before the data was spatially aggregated. Once aggregated, analysis can be categorised into the following areas; data visualisation and mapping, cluster analysis and autocorrelation, and ecological regression. The former two of these categories, data visualisation and mapping, cluster analysis and autocorrelation, use an Exploratory Spatial Data Analysis (ESDA) approach while the latter, ecological regression, uses Bayesian modelling. For all ESDA analyses, results will be given for each year as well as averaged over the three years. This is to show the overall pattern as well as how this may or may not differ by each year considered. As with previous analysis, a neighbourhood spatial weights matrix using the ‘k nearest neighbours’ conceptualisation of spatial relationships, specifying eight neighbours ($k = 8$) for each area, was constructed for this study. For details on this refer back to Chapter 5, Section 5.3.2 where the conceptualisation of spatial relationships and construction of the spatial weights matrix is discussed in further depth.

6.3.2.1 Z-score comparisons

Z-scores from the New Zealand national and urban cohorts were compared to the WHO standard to indicate relative differences in weight-for-age, height-for-age, and BMI-for-age. This enables the overall weight status within national and urban cohorts to be compared to an international standard, providing an indication of how New Zealand trends may align or differ.

6.3.2.2 Ordered logistic regression

Ordered logistic regression was applied to identify high risk groups and compare annual incidence of childhood obesity. This study utilised R, version 3.4.3 (R Core Team, 2017), to fit a regression model to an ordered factor response variable, based on BMI categories. Coefficients were converted to odds ratios and 95% confidence intervals given. It is important to note that this analysis was run on the full individual data and not on spatially aggregated data.

One of the assumptions underlying ordered logistic regression is that the relationship between each pair of outcome groups is the same, the proportional odds assumption. Put simply, this is the assumption that coefficient which describe the relationship between, for example, the highest versus lowest categories are similar of the same as the relationship between the next highest category and all lower categories. Therefore, in order to assess the appropriateness of the model, it needs to evaluated whether the proportional odds assumption in tenable. To do this the parallel slopes assumption can be evaluated by running a series of binary logistic regressions, where the original ordinal dependent variable is transformed into a binary variable, with various cut-off points of the dependent variable and then checking if coefficients are equal across these points. If the outcomes remain similar regardless of the level of the predictor variable then it can be assumed that the proportional odds assumption holds. The method outlined for testing proportional odds assumption was run for all ordered logistic regression models, with results indicating that this is a reasonable assumption for the given models.

6.3.2.3 Data visualisation and mapping

The crude rate of high weight status per 1,000 population was calculated for all urban Data Zones and mapped in quartiles. When the population composition of areas differs, for example due to demographic compositions such as age, gender or ethnicity distributions, comparing such crude rates can be erroneous because they do not take into account the distribution of the population at risk. Thus, standardised ratios are used for the comparison of two or more populations, representing a weighted average of the specific rates taken from a standard or reference population. The ethnicity adjusted expected number of those with high weight status in each area was calculated using indirect standardisation due to small counts in some population strata. As this analysis considers children within the 4 – 5 year age bracket only standardisation does not need to include age. Furthermore, as the Census (2013) does not release data on each year of age at meshblock scale, only age brackets (e.g. 0 – 5 years), it was not possible to attain an accurate representation of the 4 – 5 year old population from this data source to be used as the standard population. Because the B4SC is noted to capture a significant portion of this age group nationally, however, and comes with detailed demographic data, it serves as a good population proxy. The urban population, based on the relevant urban cohort of the B4SC, was used as the standard population for this calculation because it most closely represents the population of interest. Additionally, using this method all urban areas, for each year, are then comparable to one another. The observed number of cases divided by the expected number, given the standard population, results in a SMR. As with previous analysis, for interpretation purposes, Data Zones with a SMR below 1 have less cases of high weight status than would be expected whereas Data Zones with a SMR above 1 have more cases of high weight status than would be expected.

6.3.2.4 Cluster analysis and autocorrelation

In this analysis, as with the previous chapter, Getis Ord General G was used to investigate clustering globally and Getis Ord Gi* used to investigate clustering locally. Global statistics are used to investigate clustering in the most general sense, while local statistics are used to investigate areas in more depth. Such tools effectively analyse where there are high or low clusters of high weight status in children, including the value of the area itself in the analysis. Another important aspect that needs consideration when conducting such analysis is spatial autocorrelation which evaluates whether the spatial pattern of values is random, clustered, or dispersed. Moran's I was used to investigate autocorrelation globally, and Anselin Local Moran's I was used to investigate autocorrelation locally. These are discussed in further detail within the previous chapter (Chapter 5, Section 5.3.2.2). As with cluster analysis, global statistics are used to investigate autocorrelation in the most general sense, while local statistics are used to investigate areas in more depth. Neighbours for all analysis were defined using a spatial weights matrix based on the 'k nearest neighbours' ($k = 8$) method, as discussed previously. Importantly, the amount of any health condition is generally a function of the population density, for this reason it is most effective to run such analysis on crude rates or SMR. Therefore, instead of investigating where there are a high counts, such analysis instead investigates where there is an unexpectedly high prevalence given the population size and demographic composition of the area.

6.3.2.5 Ecological regression

Ecological regression was implemented with the aim of identifying and quantifying the effect of environmental exposures on the incidence of high weight status in 4 – 5 year old children. Regression models were run using all spatial accessibility measures and controlled for deprivation and ethnicity. The rate of environmental exposures used for this analysis is the same as that used in previous analysis (refer to Chapter 5), per 1,000 population. This is important because some areas may have a small, or no, 4 – 5 year old population but may have a large population in general and therefore a high number of exposures would be expected and must be accounted for appropriately. The deprivation measure controlled for within regression models was the Index of Multiple Deprivation No Access measure (Exeter et al., 2017). This removes the access component from the deprivation measurement and was utilised in this context because of the potential collinearity between this measure and the environmental exposure variables being tested, as discussed previously. Additionally, the observed cases in area '*k*' are assumed to be of a Poisson distribution and are modelled as Y_{kt} ~ Poisson (E_{kt},R_{kt}) where R_{kt} is the risk, relative to E_{kt}, in area *k* and year *t*. Again, '*E*' is operationally included as an offset term in the model on the natural log scale. This assumes that the observed count follows a Poisson distribution and varies over space and time.

First, a non-spatial GLM with no random effects was run on aggregated data for each year and VIF was used to detect multicollinearity among predictor variables. For this analysis, VIF values in excess of 5 were considered an indication of multicollinearity (Fox & Monette, 1992; Mason et al., 2003; Midi & Bagheri, 2010; Neter et al., 1996; PVANB, 2016). Moran's I was then used to assess the presence of autocorrelation in the residuals of the GLM models, having the null hypothesis of no autocorrelation. If spatial or temporal autocorrelation is present this violates the assumption of independence required by standard regression models. The most common remedy is an augmentation of the linear predictor which, in effect, makes the linear function of coefficients and explanatory variables greater by adding to it. In this study, spatio-temporal autocorrelated random effects are implemented as a Bayesian hierarchical model, where random effects are represented by a CAR prior (Lee, 2013).

Residual autocorrelation was accounted for by adding a set of random effects using the R package CARBayesST, version 2.5.1 (Lee, Rushworth & Napier, 2017; Lee, Rushworth & Napier, 2018). Inference was conducted in a Bayesian setting using MCMC simulation and the 'ST.CARar' model. This is a spatio-temporal model where the random effects follow a multivariate first order autoregressive time series and spatial autocorrelation is modelled via a precision matrix. This model, proposed by Rushworth, Lee and Mitchell (2014), consists of a single set of spatially and temporally autocorrelated random effects and utilises the CAR prior given by Leroux, Lei and Breslow (2000). The model is based on 20,000 post burn-in MCMC samples. It uses the same covariate and offset components as the GLM model and a binary specification of the spatial weights matrix '*W*' based on the 'k nearest neighbours' conceptualisation of spatial relationships where $k = 8$. Gaussian prior means and variances for beta parameters, defaulting to a prior mean of zero (μ_0=0) and a large prior variance, result in a prior distribution that is almost flat. The default Inverse-Gamma prior for the random effect variances τ^2, given as 1 and 0.01 for shape and scale respectively, are used. Such vague priors reflect a belief that is only weakly held and allow the observations of the data to have a dominant effect. Model fitting functions updated the random effects using the MALA algorithm (Roberts & Rosenthal, 1998). Model fit was based on DIC and model convergence based on Geweke diagnostics and the examination of trace plots.

6.4 Results

6.4.1 Cohort characteristics

When comparing results for overweight, obesity, and the combination of both categories from urban areas it can be seen that the percentage of overweight and obese children is fairly similar for all three years (Table 6.2). When considering the combined 'overweight/obese', which represents children with high weight status overall (Table 6.2), results demonstrate that roughly one in three New Zealand children aged 4 – 5 years old are of high weight status. These results also indicate that the urban cohort is a good representation of patterns found at a national scale. As shown in Table 6.2, raw counts for the overweight/obese urban cohort living in urban areas is 69.31% of the national overweight/obese cohort for 2013/14, 69.05% of the national overweight/obese cohort for 2014/15, and 69.37% of the national overweight/obese cohort for 2015/16. This indicates that the majority of children, a little over two out of three, with high weight status live in urban areas. This also aligns with research from Rajput et al. (2015) who analysed the B4SC from 2009 – 2012, finding that overweight and obesity rates were 18.3% and 16.3% respectively.

Table 6.2: *High weight status in 4 – 5 year old children**

	Overweight		Obese		Overweight/Obese	
	N	*%*	*N*	*%*	*N*	*%*
National						
2013/14	10,293	18.00	8,617	15.07	18,910	33.07
2014/15	10,118	17.94	8,759	15.53	18,877	33.47
2015/16	10,071	18.08	8,253	14.82	18,324	32.90
Urban						
2013/14	7,001	17.85	6,105	15.56	13,106	33.41
2014/15	6,910	17.79	6,124	15.77	13,034	33.56
2015/16	6,925	17.99	5,786	15.03	12,711	33.02

*Based on BMI categories

The national population used for cohort characteristics (Table 6.3) is based on the national B4SC cohort for the respective year as this is the closest accurate data for population of 4 – 5 year olds only at the scale that analysis was conducted at, as previously discussed (Section 6.3.2.3). The urban cohort constituted a fairly significant proportion of individuals in the B4SC (Table 6.3). This includes 68.90%, 69.09%, and 69.79% of the total female and

69.04%, 68.67%, and 69.22% of the total male population for 2013/14, 2014/15, and 2015/16 respectively (Table 6.3). These numbers are similar over the years considered, suggesting that roughly two thirds of both female and male populations of children aged 4 – 5 years old live in urban areas. Furthermore, the urban cohort included 67.34%, 67.30%, and 68.09% of the European/Other population, 64.33%, 63.24%, and 64.22% of the Māori population, and 90.10%, 90.01%, and 89.54% of the Pacific People total population for 2013/14, 2014/15, and 2015/16 respectively (Table 6.3). These numbers are also similar over the years considered and suggest that roughly two thirds of children who are of European/Other and Māori ethnicities are living in urban areas. Significantly more children of Pacific ethnicity are living in urban areas, however, roughly nine out of ten.

Table 6.3: *B4SC cohort characteristics*

	National			Urban			Urban Overweight/Obese		
	2013/14	2014/15	2015/16	2013/14	2014/15	2015/16	2013/14	2014/15	2015/16
Gender									
Female	27,589	27,510	27,090	19,009	19,006	18,905	5,657	5,789	5,596
Male	29,285	28,886	28,303	20,219	19,830	19,591	7,449	7,245	7,115
Ethnicity									
European/ Other	39,493	37,783	36,655	26,594	25,430	24,958	7,058	6,684	6,393
Māori	11,745	12,506	12,798	7,556	7,909	8,219	3,205	3,340	3,466
Pacific	5,636	6,107	5,940	5,078	5,497	5,319	2,843	3,010	2,852
Weight (kg)									
Mean	18.50	18.42	18.37	18.52	18.40	18.35	20.91	20.75	20.70
Std Dev	2.73	2.69	2.67	2.79	2.74	2.71	2.75	2.68	2.69
Height (cm)									
Mean	106.32	106.04	105.95	106.36	106.00	105.91	107.38	107.02	106.94
Std Dev	4.81	4.75	4.73	4.85	4.78	4.73	4.98	4.90	4.90
BMI									
Mean	16.31	16.32	16.30	16.31	16.32	16.30	18.07	18.06	18.03
Std Dev	1.61	1.60	1.58	1.64	1.63	1.60	1.30	1.29	1.29
Total	56,874	56,396	55,393	39,228	38,836	38,496	13,106	13,034	12,711

Gender and ethnicity are given as counts.

When considering children living in urban areas who have high weight status, as indicated by the 'urban overweight/obese' columns (Table 6.3), results are again fairly consistent over the three years considered for analysis. As shown (Table 6.3), this cohort constitutes 20.50%, 21.04%, and 20.66% of the total female and 25.44%, 25.08%, and 25.14% of the total male national populations for the years 2013/14, 2014/15, and 2015/16 respectively. Additionally, it constitutes 29.67%, 30.46%, and 29.60% of the total female and 36.84%, 36.53%, and 36.32% of the total male urban populations, based on the B4SC cohort, for the years 2013/14, 2014/15, and 2015/16 respectively. When considering the ethnic structure of individuals with high weight status when compared to the total B4SC cohort population consistent trends are again evident. This includes this group representing 17.87% of the European/Other, 27.29% of the Māori, and 50.44% of the Pacific People population for 2013/14, 17.69% of the European/Other, 26.71% of the Māori, and 49.29% of the Pacific People population for 2014/15, and 17.44% of the European/Other, 27.08% of the Māori, and 48.01% of the Pacific People population for 2015/16 (Table 6.3). Furthermore, this group constitutes 26.54%, 26.28%, and 25.61% of the urban European/Other population, 42.42%, 42.23%, and 42.17% of the urban Māori population, and 55.99%, 54.76%, and 53.62% of the urban Pacific Peoples population for 2013/14, 2014/15, and 2015/16 respectively, based on the total B4SC cohort. Overall, this indicates that roughly one in four children of European/Other ethnicity who are living in urban areas have high weight status, compared to roughly one in two children of Māori and Pacific People ethnic groups.

6.4.2 Z-score comparisons

As indicated by Figure 6.2, for all years both national and urban cohorts in New Zealand had higher z-scores for weight-for-age, height-for-age, and BMI-for-age than the WHO Standard. Figure 6.2 refers to pooled data for all years (2013 – 16), for annual z-score comparisons see Appendix E. While only having slightly higher values for height-for-age, the New Zealand cohort had significantly higher values for both weight-for-age and BMI-for-age. This indicates that even though New Zealand children are only slightly taller than the WHO Standard they had substantially higher weight status and BMI.

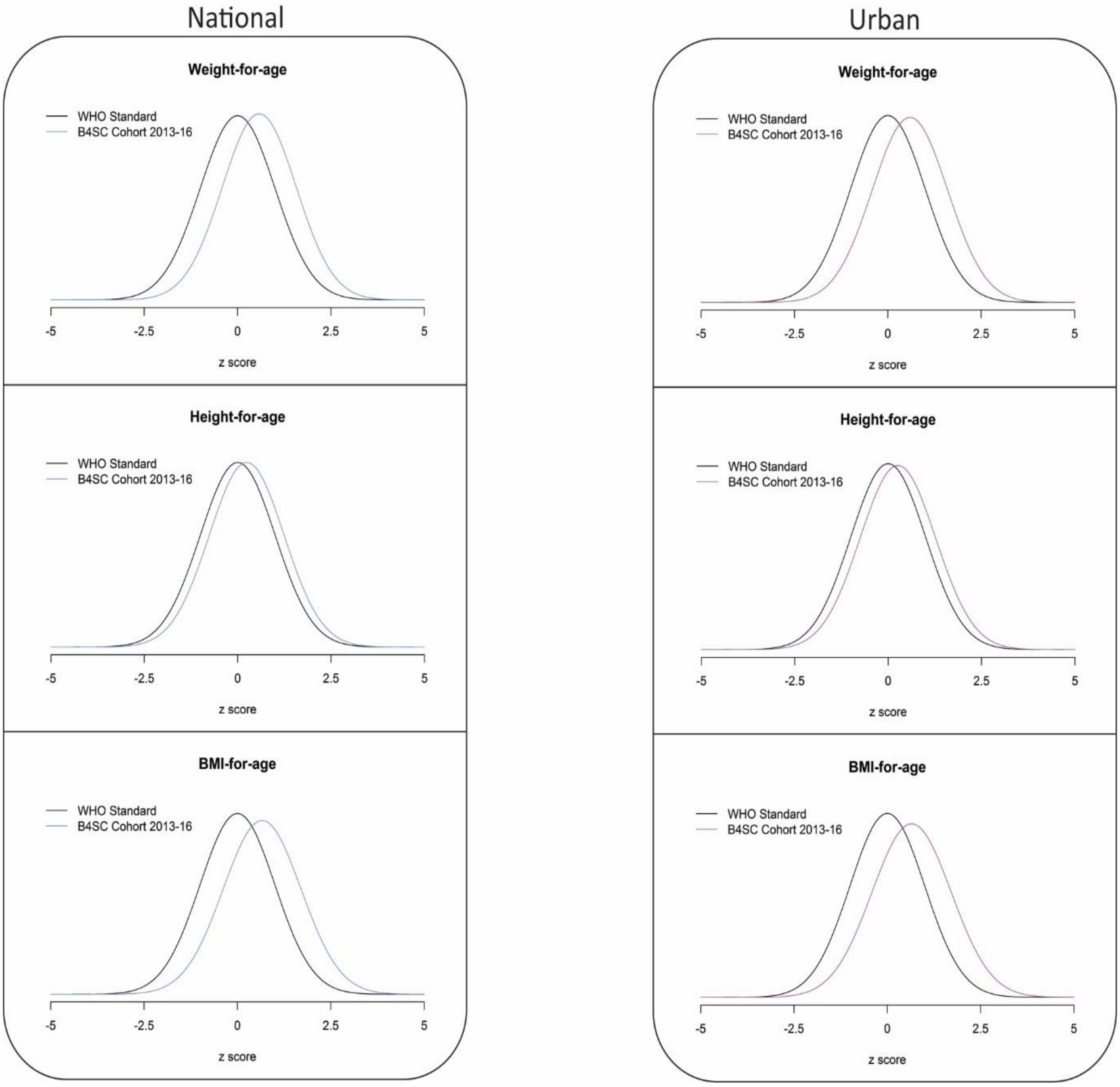

Figure 6.2: *B4SC cohort comparisons with WHO standard, based on z-score*

6.4.3 Ordered logistic regression

Ordered logistic regression analyses were applied to identify high risk groups, based on an ordered factor response variable of BMI categories, and compare annual incidence of childhood obesity based on BMI categories. For all models, females were used as the reference category for gender, European/Other was used as the reference category for ethnicity, and 2013/14 was used as the reference year.

For the national cohort, males had higher odds of having increased weight status than females (Table 6.4). Additionally, Māori are twice as likely and Pacific over three times more likely to be in a higher weight category when compared to children of European/Other ethnicities. When considering the various years of the B4SC, weight status decreased slightly (1% for 2014/15 and 4% for 2015/16, when compared to 2013/14), however this was not consistently significant. Relationships for both gender and ethnicity were significant at the <.001 level (Table 6.4). These results were also reflected in the urban cohort, however, Māori and Pacific children had slightly higher odds of increased weight status in the urban cohort as opposed to the national cohort, although relationships retained a similar nature overall. Results were very similar when considering trends from the three individual years (Appendix E).

Table 6.4: *Ordered logistic regression – B4SC all years*

	2013-16 National		2013-16 Urban	
	OR (95% CI)	*P*-value	OR (95% CI)	*P*-value
Gender				
Female	1		1	
Male	1.39 (1.36 - 1.42)	<.001	1.37 (1.34 - 1.41)	<.001
Ethnicity				
European/Other	1		1	
Māori	2.02 (1.98 - 2.07)	<.001	2.11 (2.05 - 2.18)	<.001
Pacific	3.43 (3.32 - 3.53)	<.001	3.64 (3.52 - 3.76)	<.001
Year				
2013/14	1		1	
2014/15	0.99 (0.96 - 1.01)	0.306	0.98 (0.95 - 1.01)	0.176
2015/16	0.96 (0.94 - 0.99)	0.003	0.95 (0.93 - 0.98)	0.002

6.4.4 Data visualisation and mapping

6.4.4.1 Crude rate

For 2013/14, 1.74% of urban Data Zones (n = 71) had no 4 – 5 year old population. This was similar for the following year, with 1.89% for 2014/15 (n = 77), and slightly less for the most recent year at 1.10% for 2015/16 (n = 45). The average 4 – 5 year old population for urban Data Zones was 9.59 in 2013/14, 9.50 in 2014/15, and 9.42 in 2015/16. In 2013/14, 87.97% of urban Data Zones (n = 3597) had at least one child aged 4 – 5 years with high weight status. This remained fairly similar over the following years, with 87.60% of urban Data Zones (n = 3582) having at least one child aged 4 – 5 years with high weight status in 2014/15, and 88.26% (n = 3609) in 2015/16. Finally, 12.03% of urban Data Zones (n = 492) had no children classified as being of high weight status in 2013/14. While this remained similar for 2014/15 at 12.40% (n = 507), there was a slight difference when considering the final year included for analysis, 2015/16, whereby only 11.74% of urban Data Zones (n = 480) had no children classified as being of high weight status.

Results demonstrate that, for all years, there were some Data Zones in which there were no children with high weight status while Data Zones with the largest number of children with high weight status ranged from 15 in 2015/16 to 24 in 2014/15. When considering crude rates, these ranged from 0 – 1,000 for each year as well as combined years (Figures 6.3, 6.4, 6.5 & 6.6), indicating that for all years considered there were some Data Zones where no children were overweight or obese and some where all children were overweight or obese. Given the relatively small number of 4 – 5 year old children in each Data Zone, this is an unsurprising, especially if only a small number of children are in the Data Zone.

For all urban areas, the mean rate of children with high weight status was 314.08 per 1,000 population for 2013/14, 315.17 per 1,000 population for 2014/15, and 312.53 per 1,000 population for 2015/16. This demonstrates that roughly a third of children are classified as having high weight status and reflects earlier results which showed that roughly one in three New Zealand children have high weight status (Table 6.2). There was a relatively high standard deviation for each year, indicating that data values are fairly dispersed and do not cluster around the mean. Results also demonstrated many outliers (Figures 6.3, 6.4, 6.5 & 6.6), although with considerably less when considering combined years. Overall, however, trends were fairly consistent for all years considered and averaged over combined years.

When considering individual years, the mean crude rate was lowest in Hastings and highest in Porirua in 2013/14 (Figure 6.3), lowest in Wellington and highest in Whangarei for 2014/15 (Figure 6.4), and lowest in Wellington and highest in Kapiti for 2015/16 (Figure 6.5). While Wellington seems to be a region with consistently low rates of high weight status in children there are no clear trends when considering areas of higher rates.

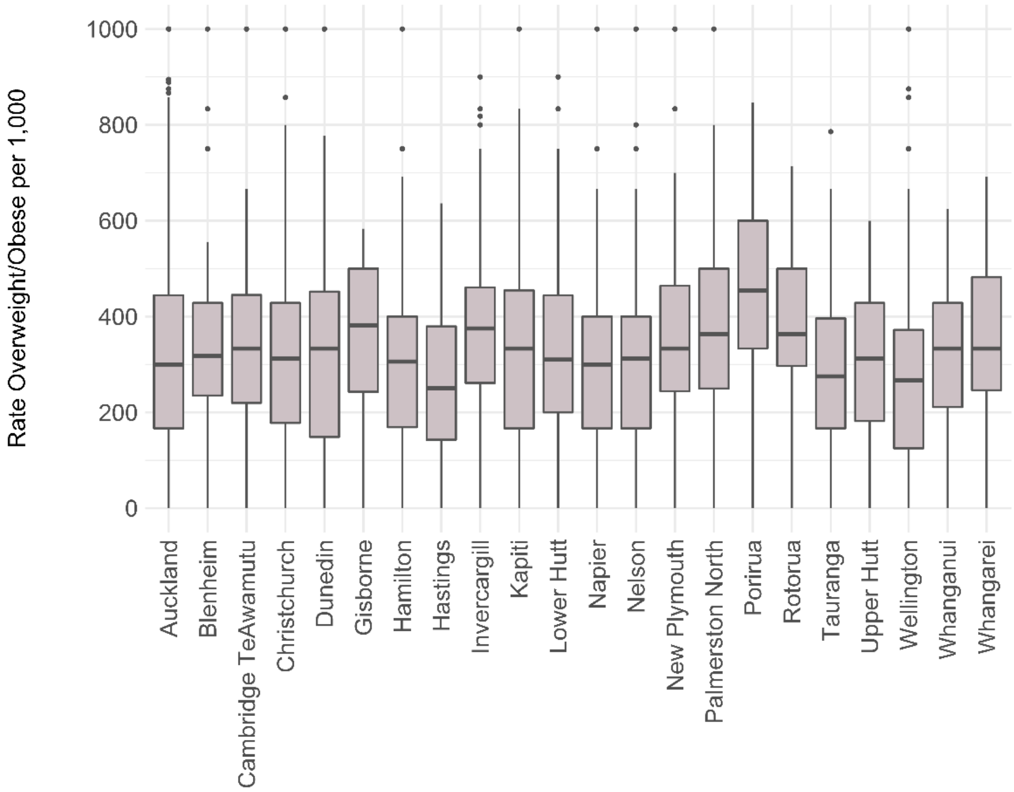

Figure 6.3: *Crude rate of high weight status in 4 – 5 year old children per 1,000 population by urban area for 2013/14*

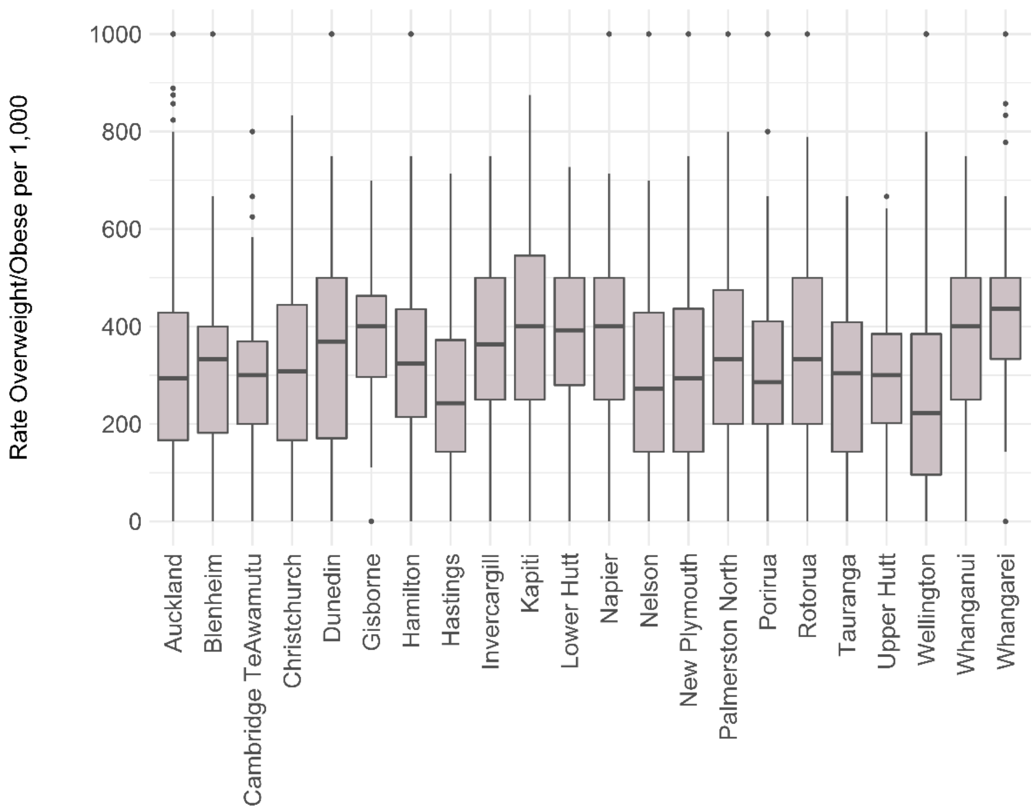

Figure 6.4: *Crude rate of high weight status in 4 – 5 year old children per 1,000 population by urban area for 2014/15*

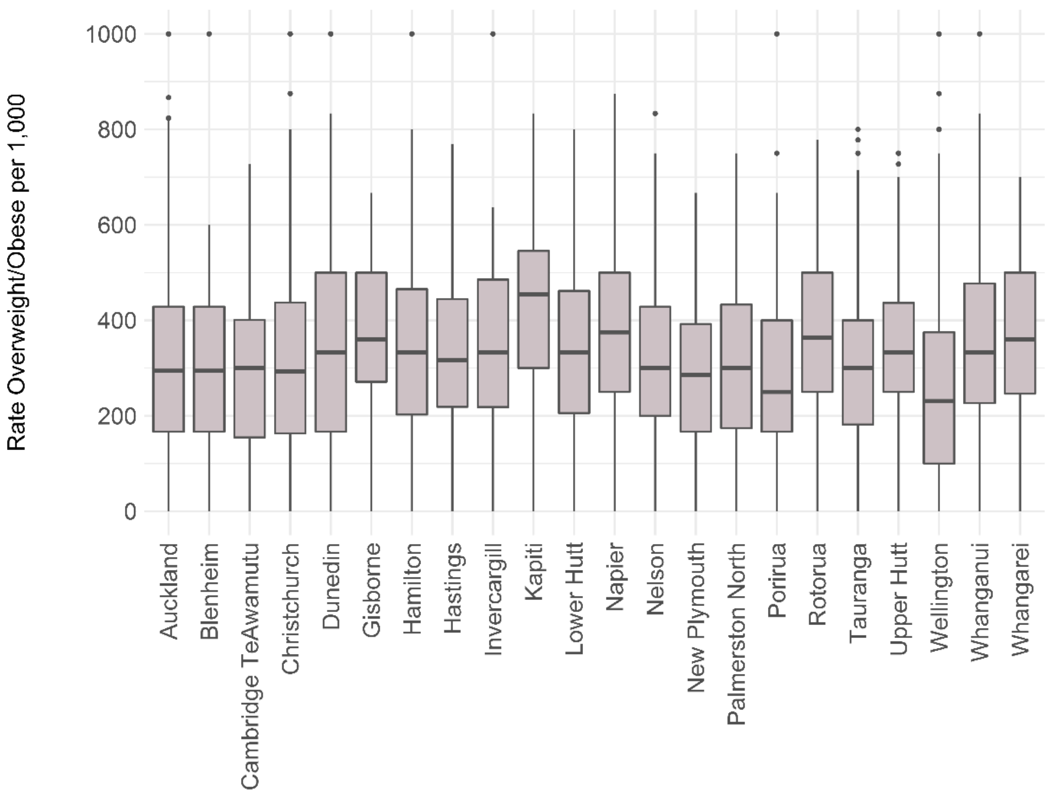

Figure 6.5: *Crude rate of high weight status in 4 – 5 year old children per 1,000 population by urban area for 2015/16*

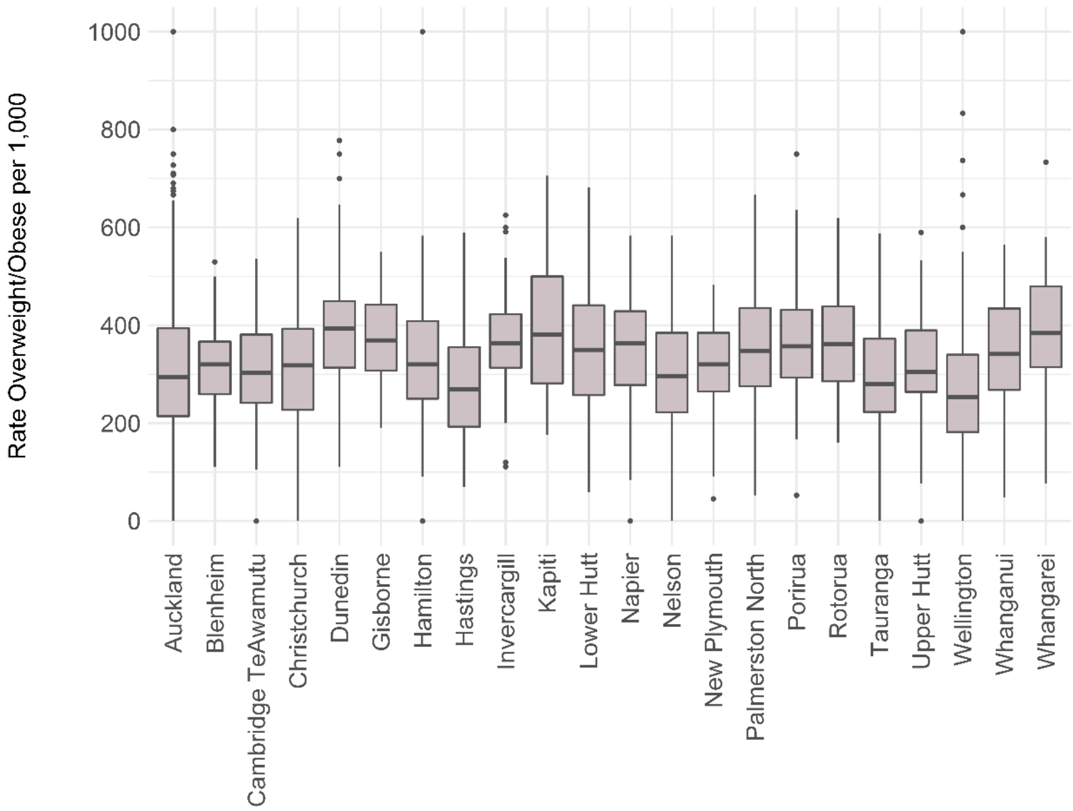

Figure 6.6: *Average crude rate of high weight status in 4 – 5 year old children per 1,000 population by urban area for 2013/16*

As with previous analysis, QQ plots were used to assess normality of the data. For further information on these refer back to Chapter 5, Section 5.4.2.1. Results confirm that the data is not normally distributed for all years, with deviations from a normal distribution particularly evident around the tails (Appendix E). This is generally expected as many Data Zones had either no children with high weight status or all children with high weight status.

A visualisation of crude rates regarding high weight status in children for the largest three urban areas of Auckland, Wellington, and Christchurch are shown in Figure 6.7, Figure 6.8, and Figure 6.9 for 2013/14, 2014/15, and 2015/16 respectively, with rates displayed by quartile. Additionally, crude rates averaged over the three years are given in Figure 6.10 while maps for all other urban areas are given in Appendix E. As shown, a visualisation of crude rates per 1,000 population indicate that all urban areas have a range of low to high rates for all years considered. The spatial pattern for all areas is fairly random with pockets of high, moderate, and low rates throughout all areas (Figures 6.7, 6.8, 6.9, 6.10 and Appendix E). Compared with 2013/14, rates for 2014/15 appear slightly higher, particularly in Wellington, Blenheim, Gisborne, Palmerston North, and Whanganui. No particular area is noticeably different, however, and overall areas continue to demonstrate a fairly mixed, random spatial pattern. There are areas such as Christchurch which demonstrate slightly decreased rates overall, although again this is not particularly noticeable. Crude rates between 2014/15 and 2015/16 are shown to be relatively similar although slightly decreased in some areas such as Whanganui, Hastings, Gisborne, and Blenheim. Patterns for Auckland, Wellington, and Christchurch also remain similar.

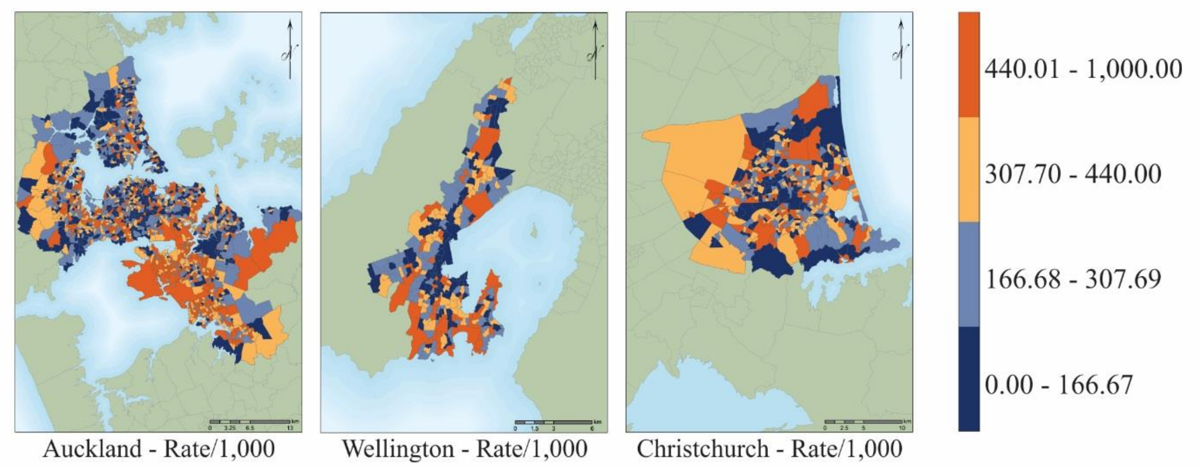

Figure 6.7: *Crude rate of high weight status in 4 – 5 year old children per 1,000 population for Auckland, Wellington, and Christchurch, 2013/14*

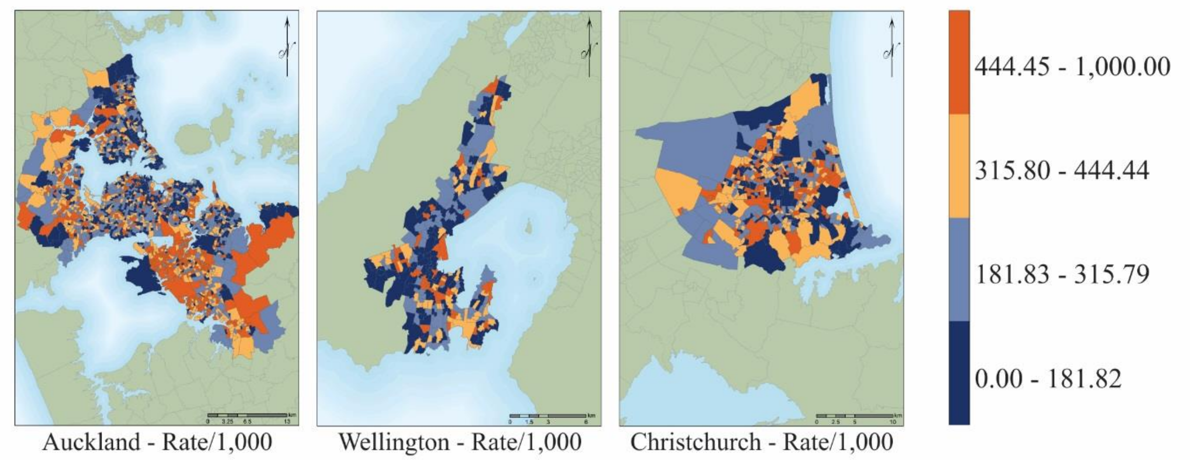

Figure 6.8: *Crude rate of high weight status in 4 – 5 year old children per 1,000 population for Auckland, Wellington, and Christchurch, 2014/15*

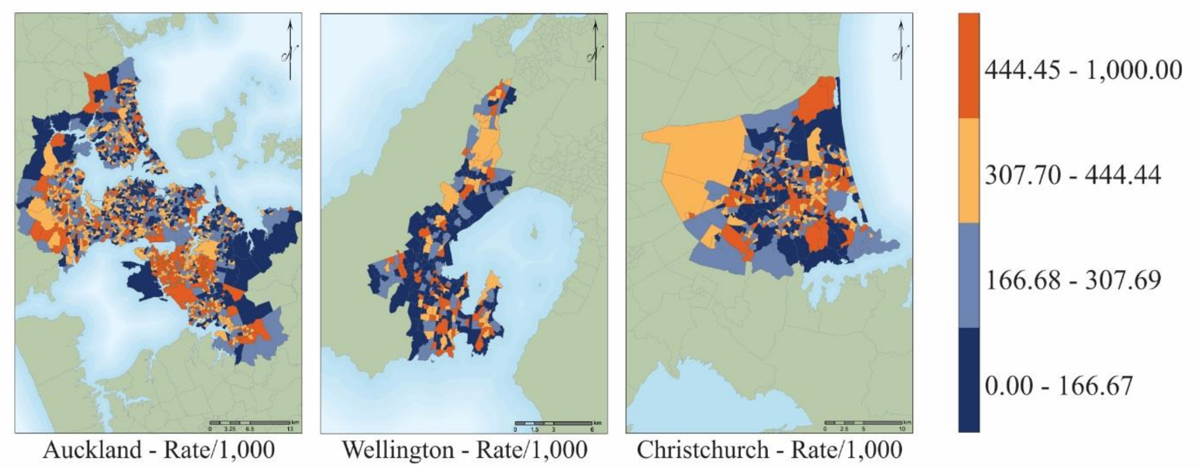

Figure 6.9: *Crude rate of high weight status in 4 – 5 year old children per 1,000 population for Auckland, Wellington, and Christchurch, 2015/16*

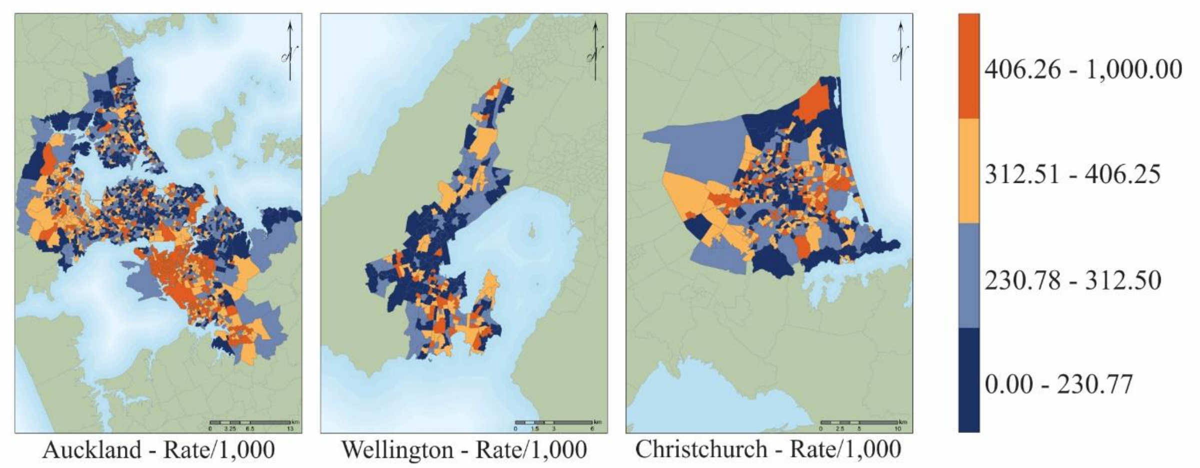

Figure 6.10: *Average crude rate of high weight status in 4 – 5 year old children per 1,000 population for Auckland, Wellington, and Christchurch, 2013/16*

Overall, spatial patterning of high, moderate, and low rates are evident throughout all urban areas for all years. While most areas demonstrated mixed results, south Auckland is the only area to demonstrate concentrated areas of high rates although this was less pronounced for 2015/16 than for previous or combined years.

6.4.4.2 Standardisation

SMR values ranged from 0 – 3.82 for all years. Results show a mean of 0.98, 0.97, and 0.96 with a standard deviation of 0.63, 0.61, and 0.60 for the years 2013/14, 2014/15, and 2015/16 respectively. Thus, the mean and standard deviation remained relatively similar for all years.

SMR values for 2013/14 demonstrates fairly stable values with some high outliers in many of the urban areas and one low outlier in Kapiti (Figure 6.11). The lowest mean SMR value was in Hastings while the highest mean SMR were in Invercargill and Porirua. Additionally, the SMR values for 2014/15 are again fairly evenly distributed across urban areas with high outliers in many areas and low outliers in Gisborne and Whangarei (Figure 6.12). The lowest mean SMR values were in Hastings and Wellington while the highest was in Whanganui. Finally, the SMR values for 2015/16 are, again, fairly evenly distributed across urban areas with high outliers in many urban areas and low outliers in Gisborne and Kapiti (Figure 6.13). The lowest mean SMR value was in Wellington while the highest mean SMR value was in Dunedin.

Interestingly, regarding the SMR values averaged over all years considered, it can be seen that is it still fairly evenly distributed across urban areas (Figure 6.14). While many urban areas exhibit low outliers Wellington shows the most extreme high outlier. Overall, the lowest mean SMR value, for all years averaged, is in Hastings while the highest mean SMR values, again for all years averaged, are in Dunedin and Whanganui.

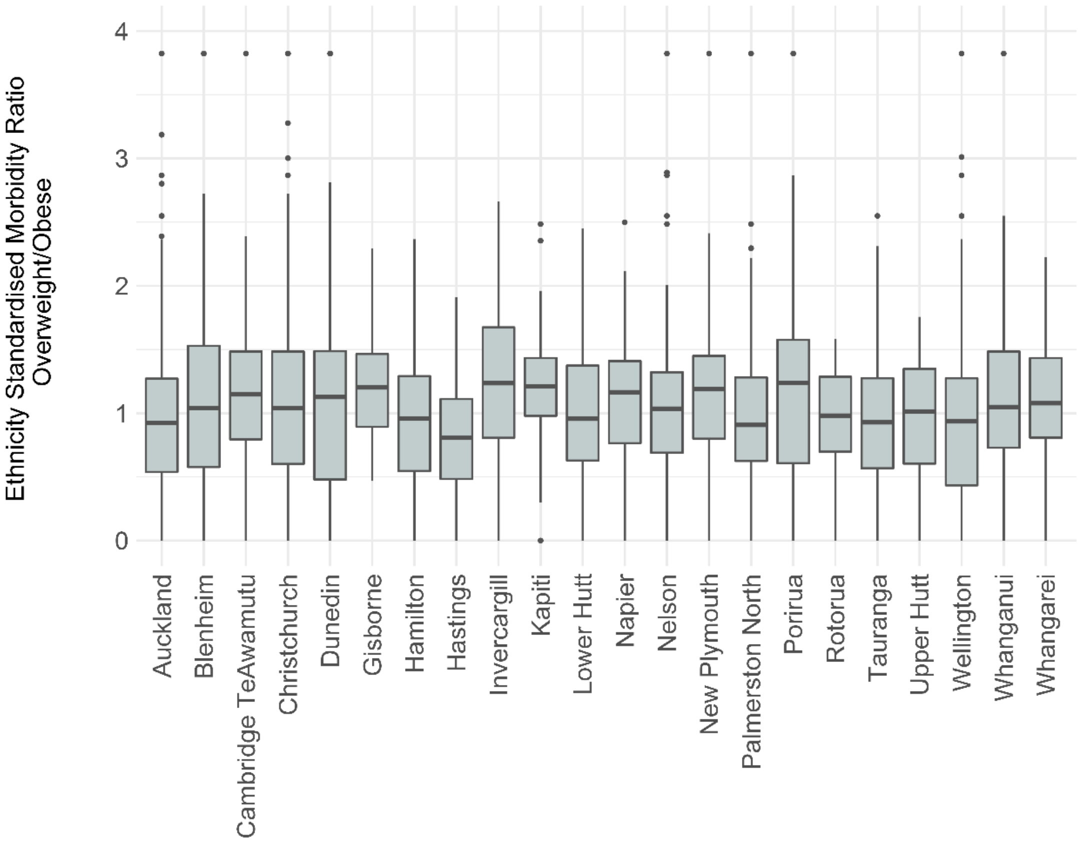

Figure 6.11: *SMR of high weight status in 4 – 5 year old children by urban area for 2013/14*

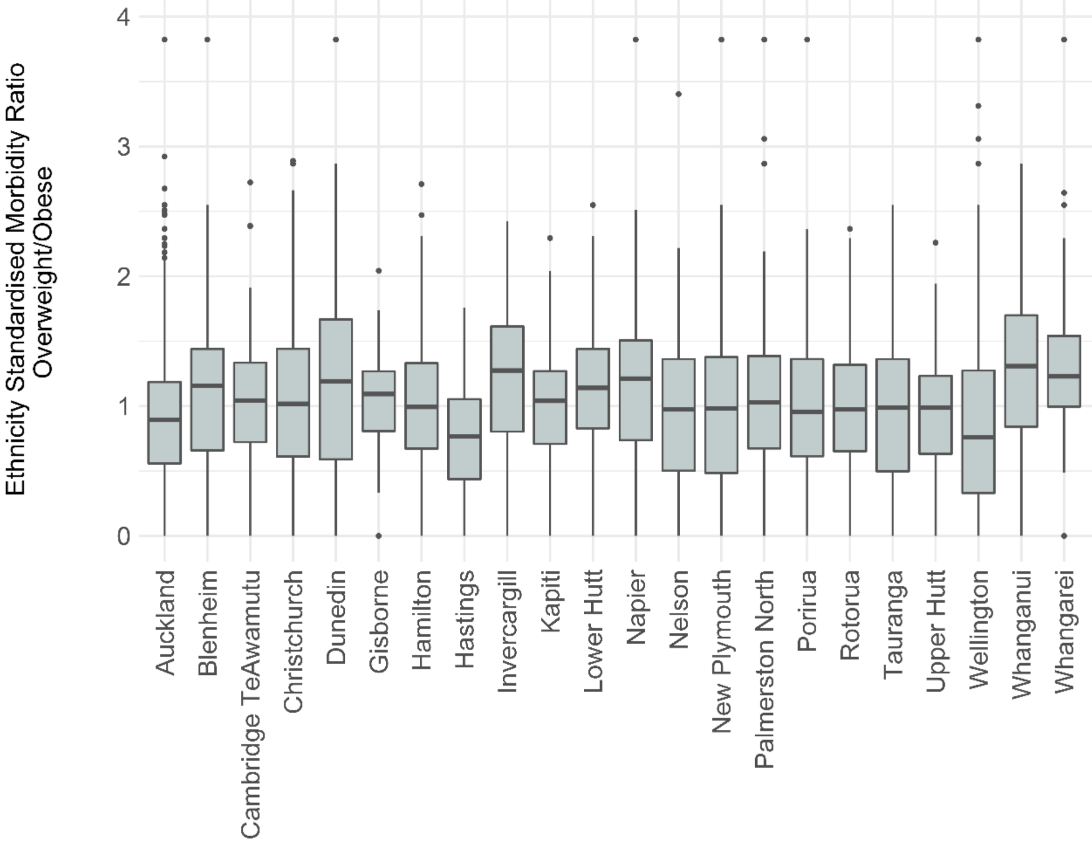

Figure 6.12: *SMR of high weight status in 4 – 5 year old children by urban area for 2014/15*

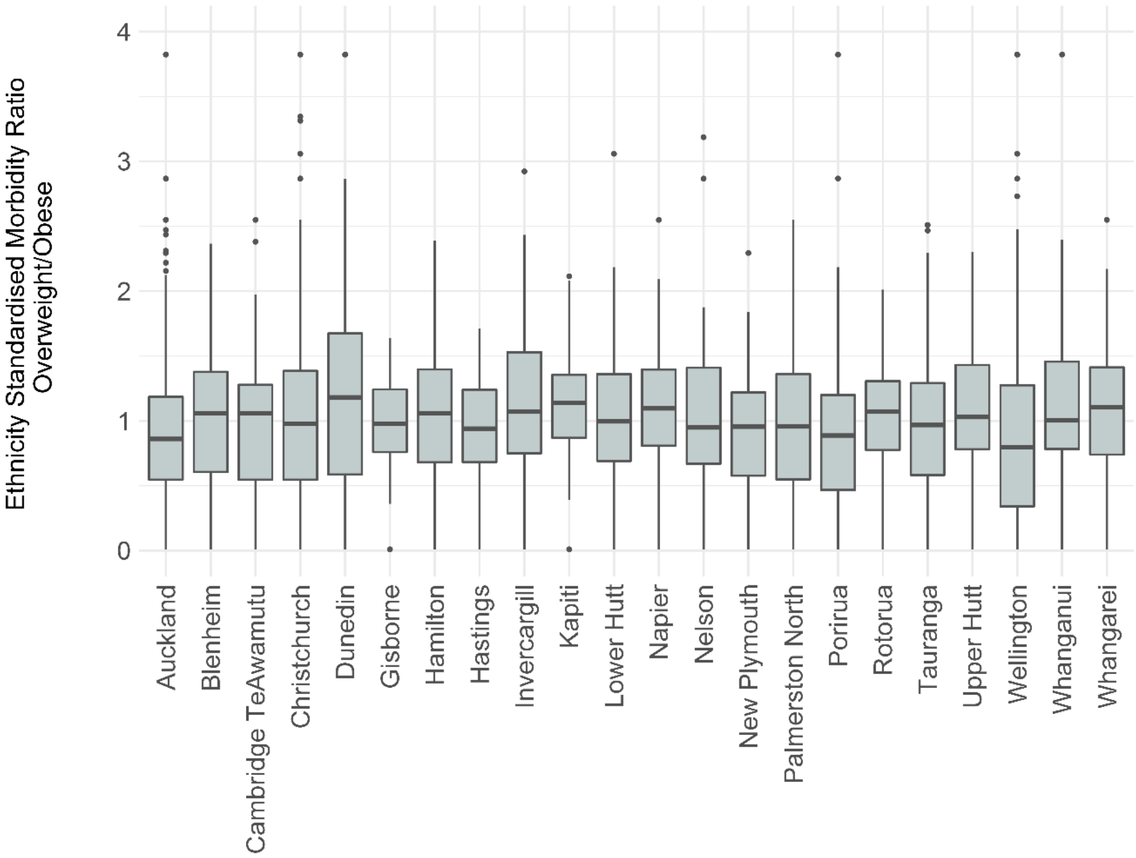

Figure 6.13: *SMR of high weight status in 4 – 5 year old children by urban area for 2015/16*

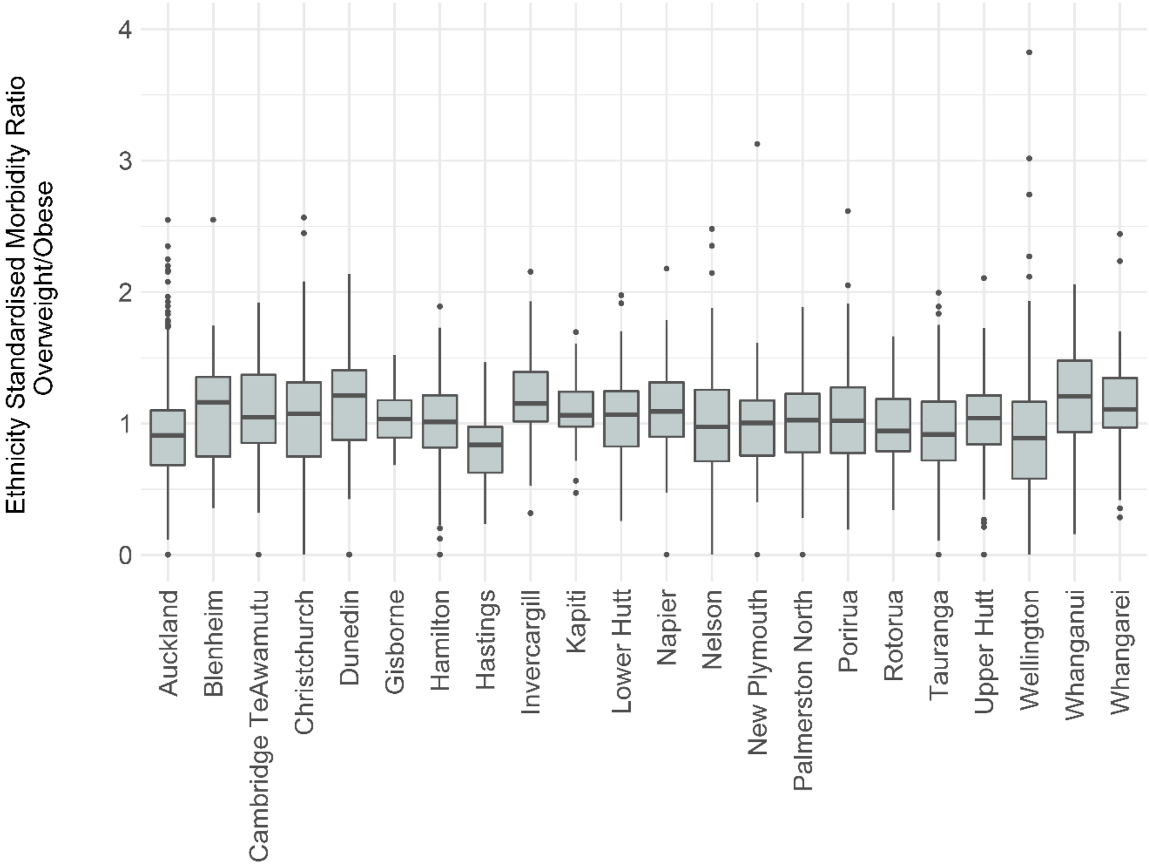

Figure 6.14: *SMR of high weight status in 4 – 5 year old children by urban area for 2013/16*

When considering SMR, QQ plots for all years demonstrate that the data are not normally distributed, with deviations from normal distribution again particularly evident around the tails (Appendix E). As discussed previously, this is generally expected as many Data Zones had either no children with high weight status or all children with high weight status.

SMR values demonstrate similar spatial patterns to that of crude rates whereby all urban areas contain a mix of low, moderate, and high values with no distinct spatial patterning (Figures 6.15, 6.16 & 6.17, and Appendix E). The spatial pattern of high rates in south Auckland has been attenuated when looking at SMR compared to crude rates, yet pockets and small clusters of high values remain as with other urban areas (Figure 6.15, Appendix E). When considering 2014/15 some urban areas such as Invercargill and New Plymouth show a slight increased value of SMR compared to both crude rates and SMR from 2013/14, however, this is not particularly pronounced (Figure 6.16, Appendix E). Additionally, values in Invercargill, Blenheim, Gisborne, and Whanganui decreased slightly for 2015/16, although not noticeably so (Appendix E). Furthermore, SMR values in Christchurch have decreased in the north-west, but increased throughout the city centre and south. Values in the south east of Auckland have also decreased while Wellington remains fairly similar overall (Figure 6.17). Finally, the SMR averaged over all years considered in this analysis demonstrates a relatively similar spatial pattern to that of the individual years whereby all urban areas contain a mix of low, moderate, and high values and no clear spatial pattern is defined (Figure 6.18, Appendix E). Auckland, Wellington, and Christchurch demonstrate spatial patterns which are very mixed and this is largely reflected in other urban areas.

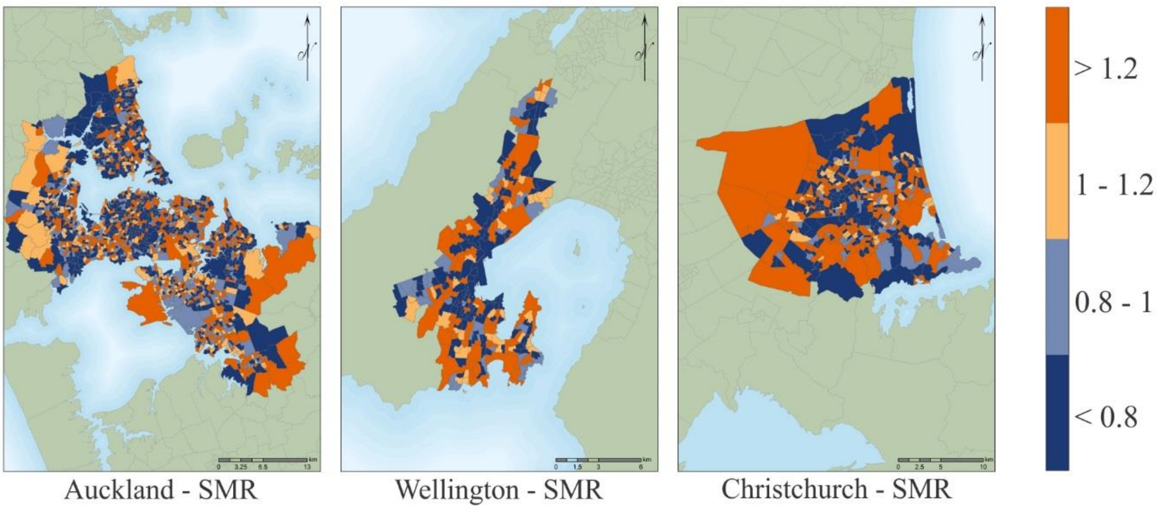

Figure 6.15: *SMR of high weight status in 4 – 5 year old children for Auckland, Wellington, and Christchurch, 2013/14*

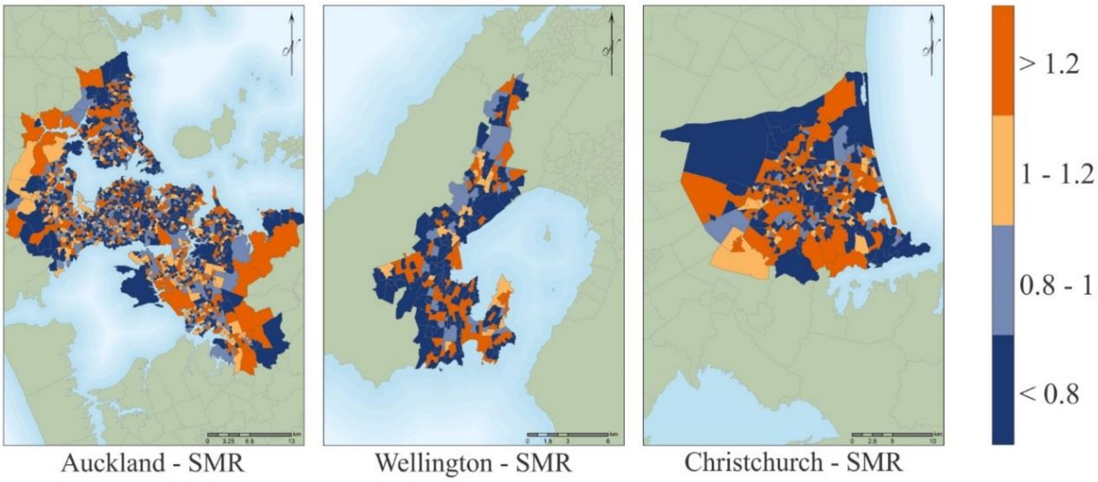

Figure 6.16: *SMR of high weight status in 4 – 5 year old children for Auckland, Wellington, and Christchurch, 2014/15*

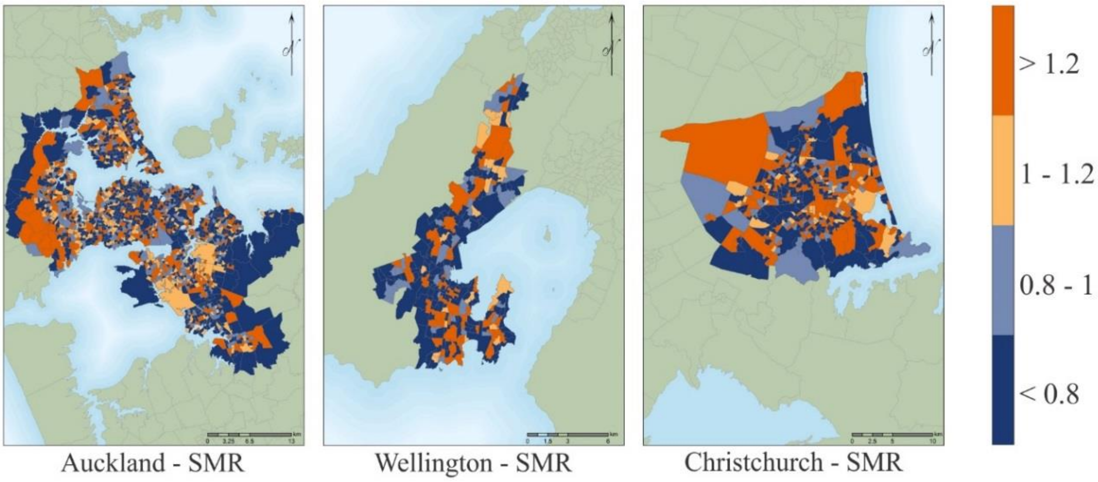

Figure 6.17: *SMR of high weight status in 4 – 5 year old children for Auckland, Wellington, and Christchurch, 2015/16*

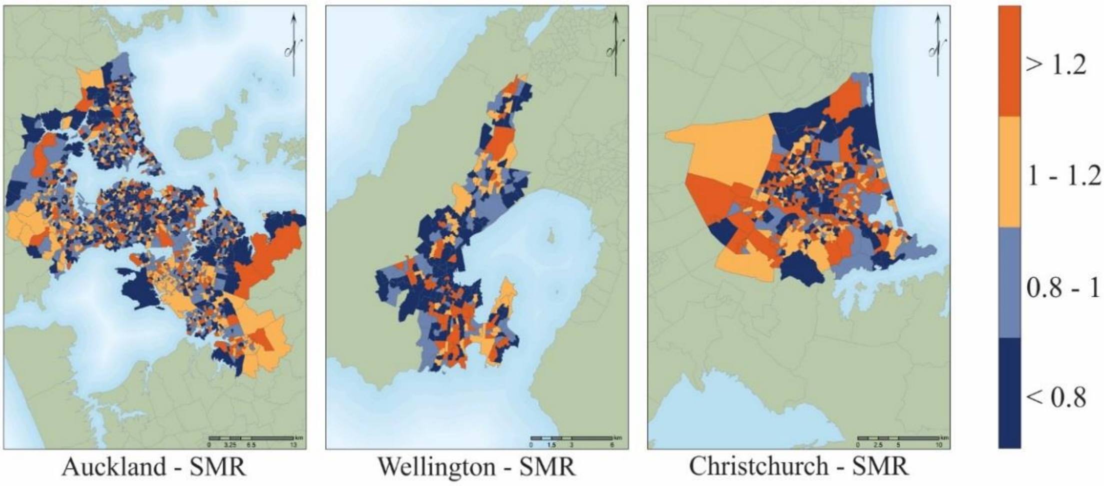

Figure 6.18: *Average SMR of high weight status in 4 – 5 year old children for Auckland, Wellington, and Christchurch, 2013/16*

6.4.5 Cluster analysis and autocorrelation

6.4.5.1 Clustering

A pivotal aspect of ESDA is assessing spatial clustering to determine if there are high or low clusters in the data (see Chapter 5, Section 5.4.3 for further detail). The null hypothesis, and point of reference, is that of spatial randomness which suggests that there is no relationship between data values and spatial location. Alternatively, positive results suggest there are clusters of higher than expected values present and negative results suggest there are clusters of lower than expected values present within the dataset. As indicated, global clustering results are significant for both measures of high weight status in children (rate/1,000 and SMR), indicating high clusters for individual and combined years (Table 6.5). Results, however, are attenuated for SMR when compared to rate/1,000.

Table 6.5: *Global clustering of high weight status in 4 – 5 year old children*

	General G	*Z*-score*	*P*-value	Hypothesis
2013/14				
Rate/1,000	0.000261	15.194	<0.001	alternative (high clusters)
SMR	0.000249	4.409	<0.001	alternative (high clusters)
2014/15				
Rate/1,000	0.000262	16.139	<0.001	alternative (high clusters)
SMR	0.000253	7.826	<0.001	alternative (high clusters)
2015/16				
Rate/1,000	0.000261	15.111	<0.001	alternative (high clusters)
SMR	0.000251	6.362	<0.001	alternative (high clusters)
2013/16				
Rate/1,000	0.000259	23.896	<0.001	alternative (high clusters)
SMR	0.000250	10.513	<0.001	alternative (high clusters)

*3 d.p.

Given the above z-scores and p-values there is less than a 1% likelihood that this clustered pattern could be the result of random chance. Thus the null hypothesis or spatial randomness may be rejected here, as the spatial distribution of high and/or low values in the dataset is more spatially clustered then would be expected if the underlying spatial processes were random. Yet, this only indicates the presence of spatial clustering globally. In order to determine such information local methods are using Getis Ord Gi*.

Results for 2013/14 demonstrate that the spatial pattern of local clustering is fairly random with pockets of hot and cold spots throughout urban areas for both crude rate per 1,000 and SMR (Figure 6.19, Appendix E). Generally, hot spots are more frequently observed than cold spots. Regarding the three main urban areas of Auckland, Wellington, and Christchurch for 2013/14 the local clustering pattern is fairly random, with pockets of hot and cold spots throughout these urban areas (Figure 6.19). For crude rate per 1,000, Auckland demonstrates pockets of cold spots in the north, west, and central areas and areas of hot spots in the south. Meanwhile, Christchurch and Wellington demonstrate only small pockets of hot and cold spots. These spatial patterns were largely reflected in SMR results, however, notable differences are an increase in hot spots for the north west of Christchurch and a decrease in hotspots for the south Auckland area (Figure 6.19). Regarding other urban areas, as noted, the spatial pattern is fairly random for both crude rate and SMR (Appendix E). While some hot spots and cold spots are shown, there is no clear spatial pattern.

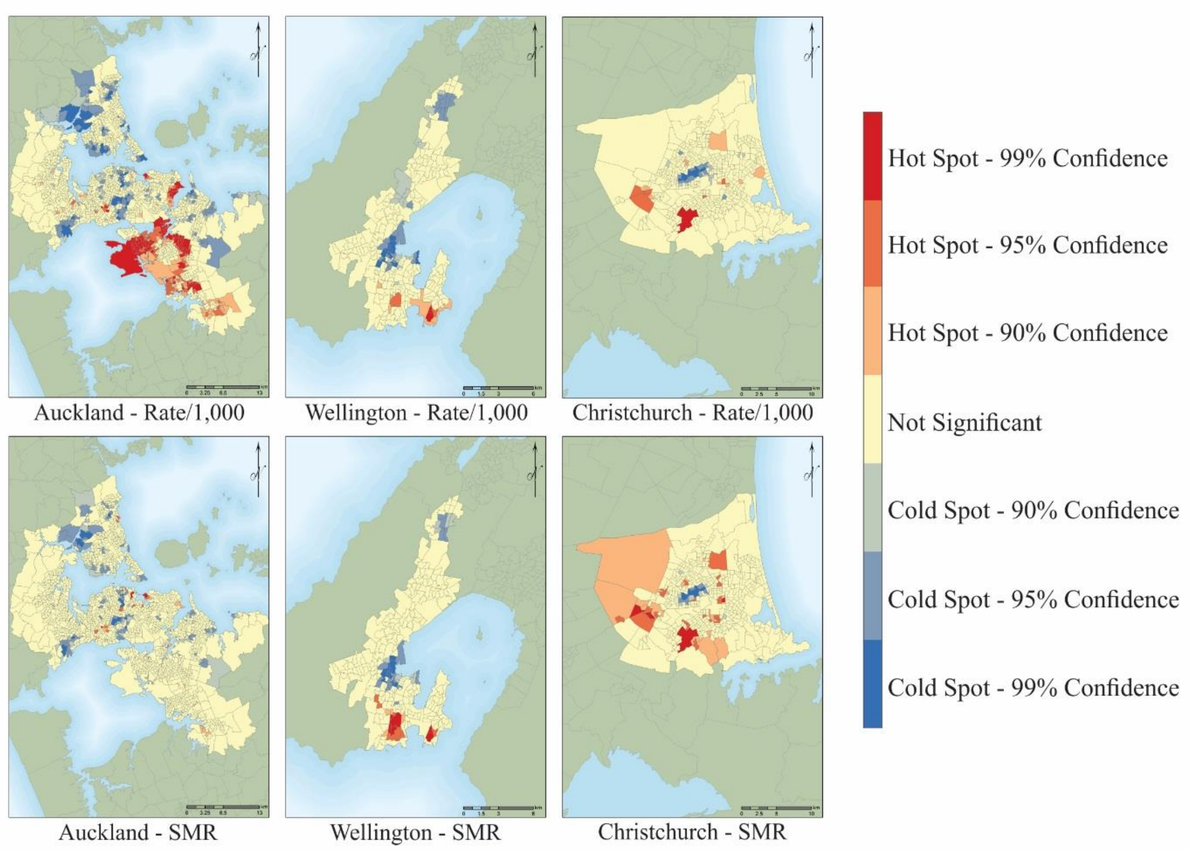

Figure 6.19: *Spatial clustering of high childhood weight status for Auckland, Wellington, and Christchurch 2013/14*

Additionally, results for 2014/15 demonstrate fairly random spatial patterning of hot and cold spots for both crude rate per 1,000 and SMR (Figure 6.20, Appendix E). As with the previous year, hot spots are more frequently observed than cold spots. Regarding the three main urban areas of Auckland, Wellington, and Christchurch the local clustering pattern is fairly random, with pockets of hot and cold spots throughout these urban areas (figure 6.20). For crude rate per 1,000, Auckland demonstrates cold spots in the north and central areas and hot spots in the south. Christchurch demonstrates small pockets of hotspots, particularly in the east and south west and cold spots in the central city only while Wellington largely demonstrates cold spots throughout central areas (Figure 6.20). This was true for both crude rates and SMR, however, hotspots within south Auckland were attenuated when considering SMR apart from one notable area in the far south. Regarding other urban areas, as noted, the spatial pattern is fairly random for both crude rate per 1,000 and SMR (Appendix E). The exception to this is Whangarei and to a lesser degree Dunedin, which demonstrate significant areas of hot spots (Appendix E). With the exception of significant hotspots throughout Whangarei, this is a fairly similar spatial pattern seen as for 2013/14 results.

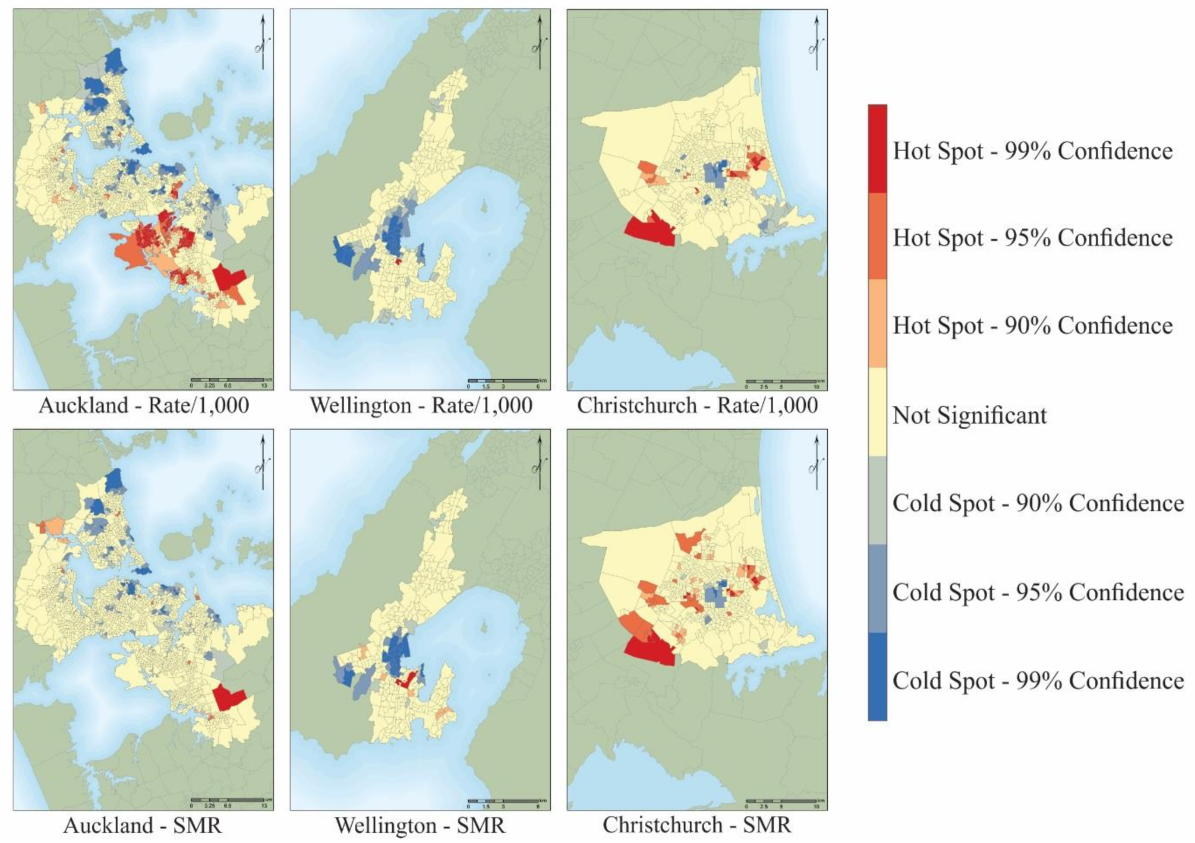

Figure 6.20: *Spatial clustering of high childhood weight status for Auckland, Wellington, and Christchurch 2014/15*

Results for 2015/16 mirror previous results whereby the spatial patterns of local clustering are fairly random, with pockets of hot and cold spots for both crude rate per 1,000 and SMR (Figure 6.21, Appendix E). Regarding the three main urban areas of Auckland, Wellington, and Christchurch the local clustering pattern is again fairly random, with pockets of hot and cold spots throughout these urban areas (Figure 6.21). For crude rate per 1,000, Auckland demonstrates cold spots in the north and central areas and hot spots in the south, as with previous years. Wellington largely demonstrates cold spots while Christchurch demonstrates one pocket of high clusters in the east and pockets of low clusters in the central and south of the city. This was largely reflected in SMR results, however, the hot spots in south Auckland and the cold spots in south Christchurch were no longer significant when looking at SMR (Figure 6.21). Regarding other urban areas, the spatial pattern is fairly random for both crude rate per 1,000 and SMR (Appendix E). Whangarei and Dunedin again show hot spots, similar to the previous year, as do Hutt Valley and Kapiti. Results for Kapiti are only significant when considering crude rate per 1,000, however, not SMR (Appendix E).

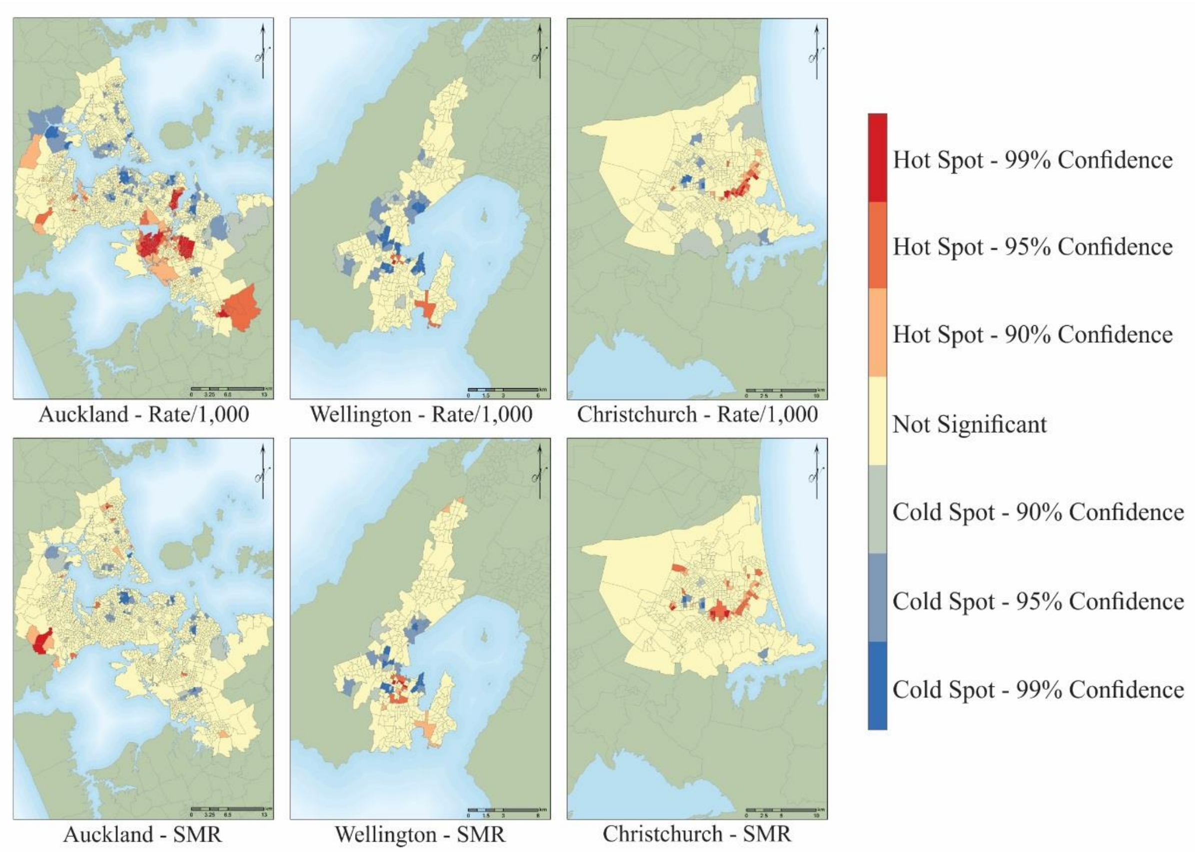

Figure 6.21: *Spatial clustering of high childhood weight status for Auckland, Wellington, and Christchurch 2015/16*

Results for spatial clustering averaged over all three years of data are reflective of individual years (Figure 6.22 and Appendix E). Regarding Auckland, Wellington, and Christchurch results for combined years show concentrated areas of hot spots in southern Auckland, but only when considering crude rates (Figure 6.22). These hot spots are no longer significant when considering SMR. Pockets of significant cold spots are visible throughout all three areas, however, these are less frequently observed in Christchurch than Wellington and Auckland, particularly for SMR (Figure 6.22). Further, regarding other urban areas the most notable areas of hot spots for combined years are seen in Invercargill, Dunedin, and Whangarei (Appendix E). Overall, results for all years, over all urban areas, demonstrate fairly random spatial patterning.

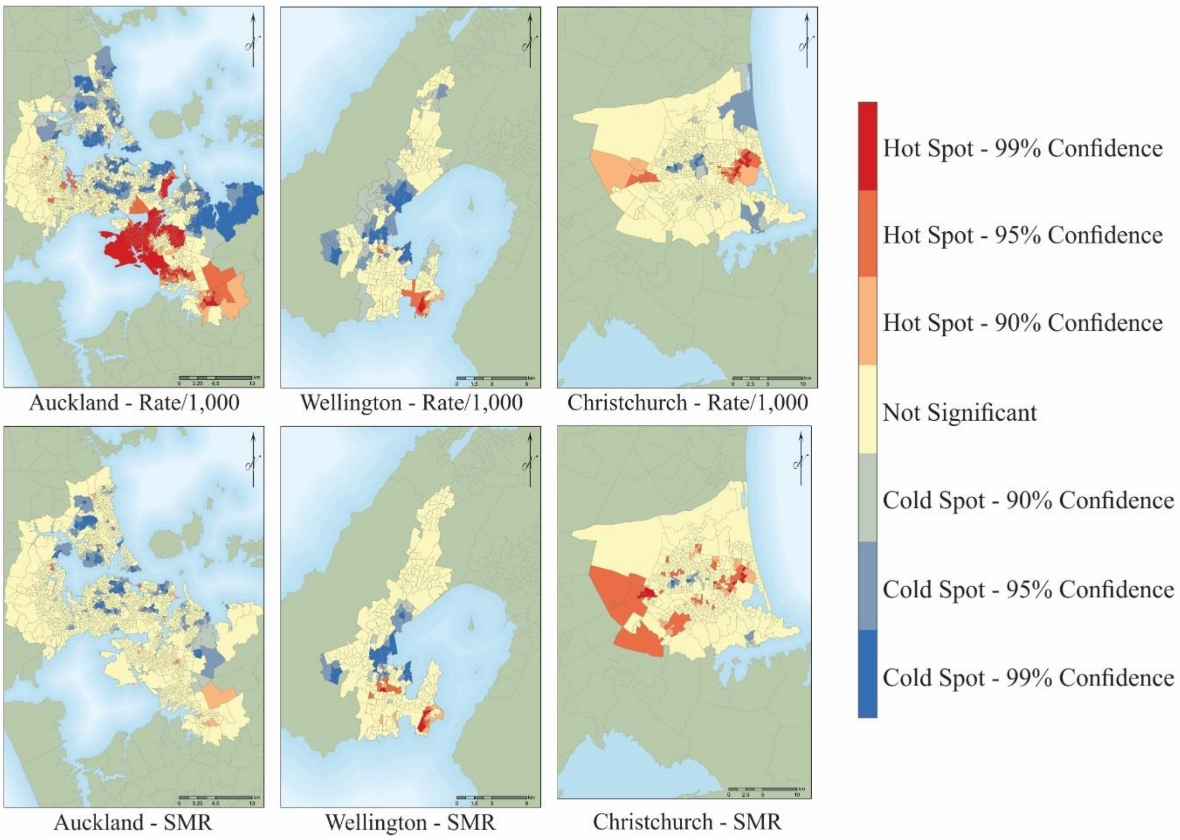

Figure 6.22: *Spatial clustering of high childhood weight status for Auckland, Wellington, and Christchurch 2013/16*

6.4.5.2 Autocorrelation

As discussed in Chapter 5, another pivotal features of ESDA is that of spatial autocorrelation which determines if geographical proximity has an influence on the values of a dataset using the Moran's I statistic. The null hypothesis, and point of reference, for spatial autocorrelation methods is that of spatial randomness which suggests that there is no relationship between the data values and spatial location. Alternatively, positive spatial autocorrelation suggests spatial clustering and negative spatial autocorrelation suggests that there are spatial outliers within the dataset (Anselin, 2000). As discussed within Chapter 5, Moran's I statistic is, in essence, a cross-product statistic between a variable and its spatial lag. For further detail about spatial autocorrelation and the Moran's I coefficient refer back to Chapter 5, Section 5.4.3.2. Table 6.6 and Appendix E demonstrate that Moran's I statistics are significant for all measures of urban childhood high weight status for both individual and combined years, indicating substantial clustering. Results show, however, that clustering is stronger for crude rate per 1,000 than SMR which was less clustered, yet still significant overall (Table 6.6).

Table 6.6: *Global autocorrelation – B4SC 2013-16*

	Moran's I	*Z*-score*	*P*-value	Hypothesis
2013/14				
Rate/1,000	0.145742	19.690	<0.001	alternative (clustered)
SMR	0.046238	6.271	<0.001	alternative (clustered)
2014/15				
Rate/1,000	0.158906	21.465	<0.001	alternative (clustered)
SMR	0.075142	10.169	<0.001	alternative (clustered)
2015/16				
Rate/1,000	0.134046	18.113	<0.001	alternative (clustered)
SMR	0.043564	5.910	<0.001	alternative (clustered)
2013/16				
Rate/1,000	0.292790	39.527	<0.001	alternative (clustered)
SMR	0.124071	16.770	<0.001	alternative (clustered)

*3 d.p.

As the p-value is statistically significant and the z-score is positive the null hypothesis may be rejected as the spatial distribution of values in the dataset is more spatially clustered than would be expected if the underlying spatial processes were random. When considering local autocorrelation for 2013/14, the three main urban areas of Auckland, Wellington, and

Christchurch demonstrate a fairly random pattern, with pockets of all categories throughout these areas (Figure 6.23). The central and south west of Christchurch showed significant results, as did central and northern Wellington and many areas of Auckland, predominately central and southern. Notable differences between crude rate per 1,000 and SMR are that Christchurch and Wellington SMR results indicate more low-high outliers than rate alone and Auckland SMR results indicates less high-high clusters in the south than rate alone (Figure 6.23). Regarding other urban areas, as noted, the spatial pattern is fairly random for both crude rate per 1,000 and SMR (Appendix E).

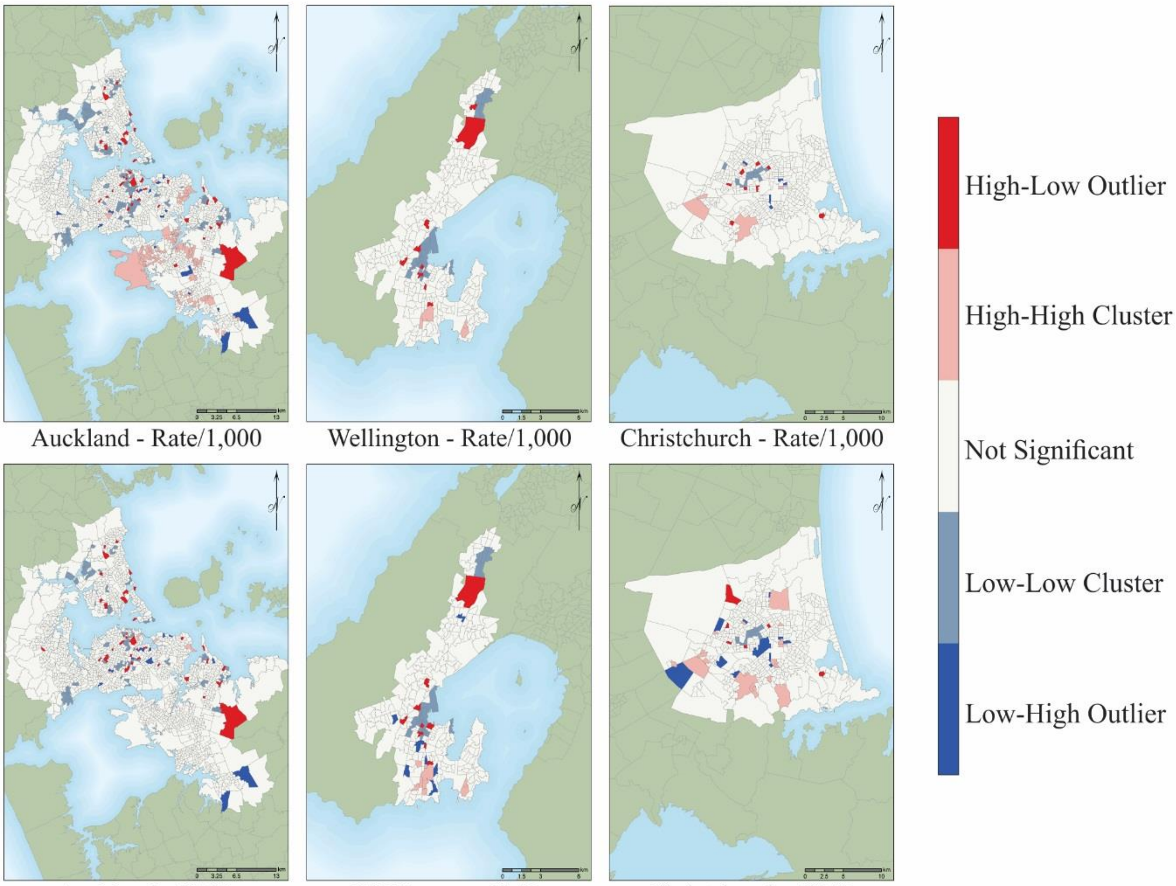

Figure 6.23: *Spatial autocorrelation of high childhood weight status for Auckland, Wellington, and Christchurch 2013/14*

For 2014/15, the three main urban areas of Auckland, Wellington, and Christchurch demonstrate a local spatial autocorrelation pattern which is fairly random, with pockets of all categories throughout these areas (Figure 6.24). The central areas of Christchurch and Wellington demonstrated significant results for both crude rate per 1,000 and SMR. The north, central, and south of Auckland showed significant results for crude rate per 1,000, however, these were less significant when considering SMR, with only small pockets remaining throughout (Figure 6.24). Regarding other urban areas, again, the spatial pattern is fairly random for both crude rate per 1,000 and SMR (Appendix E).

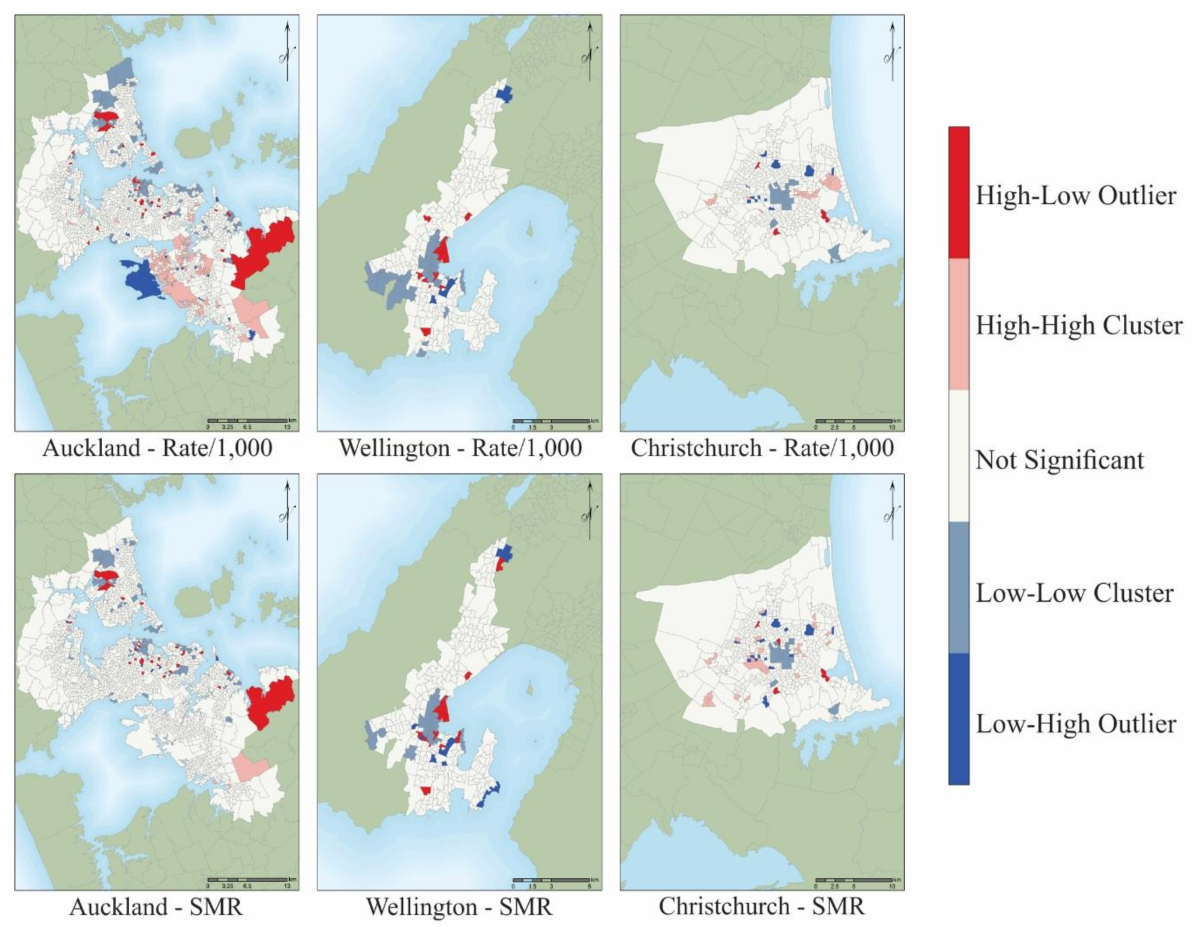

Figure 6.24: *Spatial autocorrelation of high childhood weight status for Auckland, Wellington, and Christchurch 2014/15*

When considering results from 2015/16, the three main urban areas of Auckland, Wellington, and Christchurch again demonstrate a fairly random pattern, with pockets of all local spatial autocorrelation categories (Figure 6.25). The central areas of Christchurch and Wellington demonstrated significant results for both crude rate per 1,000 and SMR. Additionally, Auckland showed significant results for crude rate per 1,000, however, these were less significant when considering SMR with only small pockets remaining throughout (Figure 6.25). Regarding other urban areas, as with results from previous years, the spatial pattern is fairly random for both crude rate per 1,000 and SMR (Appendix E).

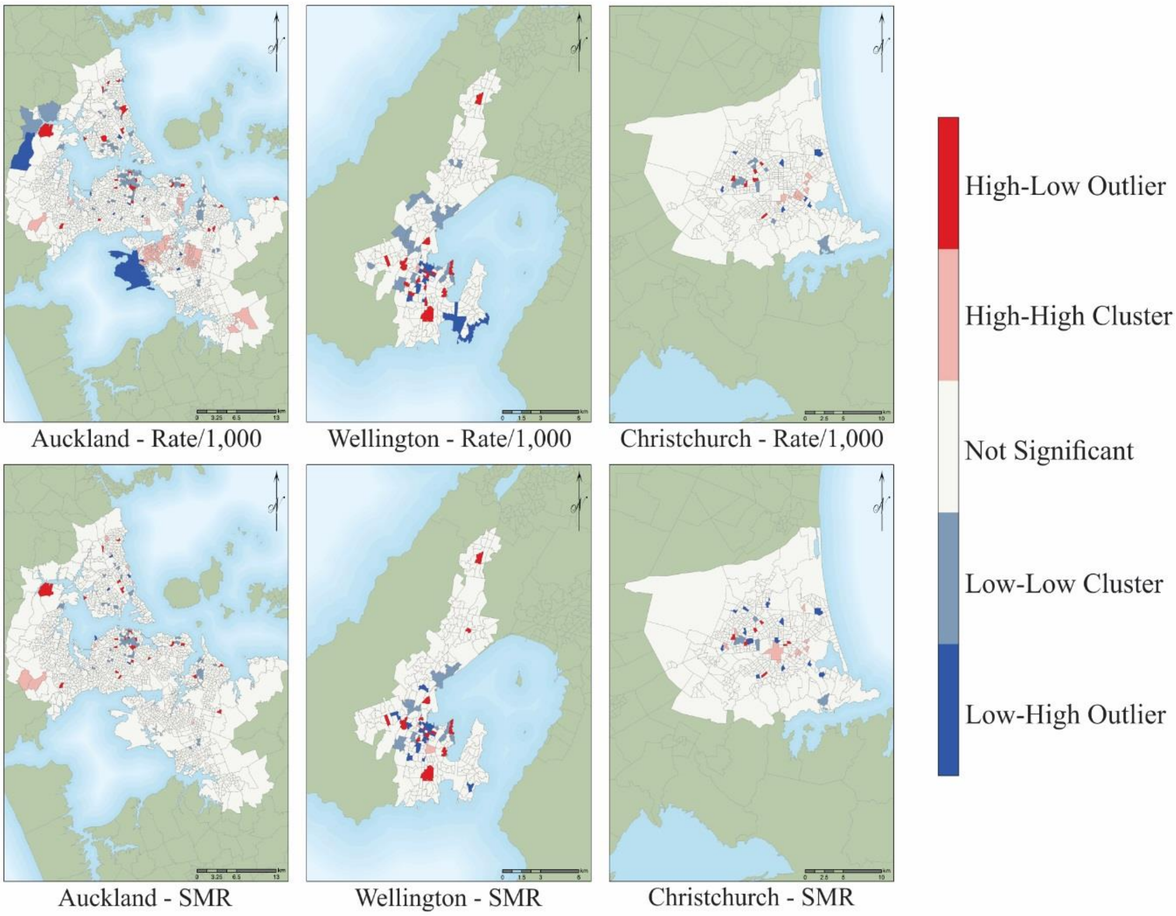

Figure 6.25: *Spatial autocorrelation of high childhood weight status for Auckland, Wellington, and Christchurch 2015/16*

Finally, results of local autocorrelation for combined years are reflective of results for individual years for Auckland, Wellington, and Christchurch with pockets of all autocorrelation categories and a fairly random spatial distribution (Figure 6.26). High clusters were more frequently observed when considering crude rates while outliers were more frequently observed when considering SMR (Figure 6.26). Additionally, low clusters were noticeable throughout results for both crude rate and SMR. Regarding other urban areas, the spatial distribution of local autocorrelation categories is fairly randomly distributed for both crude rates and SMR, as with results from individual years (Appendix E).

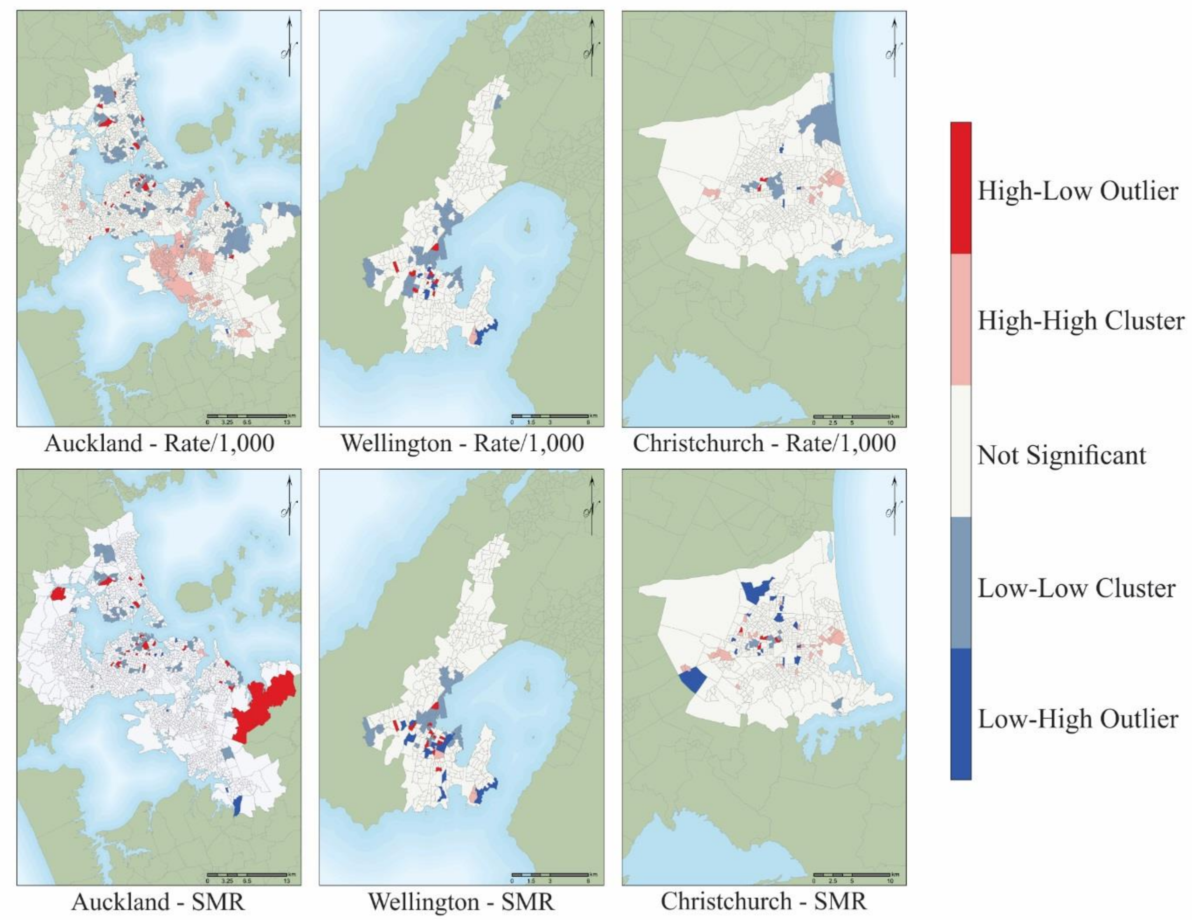

Figure 6.26: *Spatial autocorrelation of high childhood weight status for Auckland, Wellington, and Christchurch 2013/16*

Overall, for all years considered the spatial pattern of local autocorrelation is fairly random, with pockets of all cluster/outlier categories throughout urban areas for both crude rate per 1,000 and SMR (Figures 6.23, 6.24, 6.25, 6.26 and Appendix E). While local spatial autocorrelation does show some significant results, the spatial pattern is fairly random and does little to identify particular areas with consistent results.

6.4.6 Ecological regression

For ecological regression models, the data on childhood weight status are population level counts of the number of children aged 4 – 5 year olds who are of high weight status. This includes children of both overweight and obese status. The observed number in each Data Zone are, however, dependent on the size and demographic structure of the 4 – 5 year old population living there. This is adjusted for using indirect standardisation which computes the number which would be expected if national ethnicity rates applied. As with previous analysis, operationally this is included in the model as an offset term on the natural log scale. In summary, this means that when considering the number of 4 – 5 year old children with high weight status the model takes into account not only the overall population size of this age group in each area, but also the ethnicity-specific demographic structure. All models also account for area-level deprivation.

Additionally, as with previous analysis, the continuous rate of environmental exposures led to the best model fit over all other measures tested (tertiles, quartiles, and quintiles). For this reason, and to align with exposure metrics used in previous analysis, the continuous variable for environmental exposures were used as the final environmental variable in buffer analysis. For analysis regarding the E2SFCA, environmental exposures were measured on a continuous scale from 0 – 5, as discussed in Chapter 4, Section 4.3.2. The greenspace measure was not included for the E2SFCA model as greenspace itself was measured as a percentage within buffers. Because there was no equivalent measure for greenspace using the E2SFCA, however, it is omitted from this model.

Furthermore, regression models contained all environmental variables so that given coefficients are conditional on all variables. As with previous analysis, the only models which exhibited significant multicollinearity, based on a VIF cut-off value of 5, were the 3000 metre buffers where collinearity was detected for the fast food and takeaway categories (Appendix E). These variables were then fit to separate models as to not affect results, however, for ease of presentation and interpretation all results are shown in one table.

Significant spatial autocorrelation of residuals was present in all ecological GLM regression models, both by individual year and combined years (Table 6.7). This indicates that the assumption of independence is not withstanding, a typical occurrence with spatial data where neighbouring areas tend to have similar values.

Table 6.7: *Residual autocorrelation from non-spatial models*

Model	Moran's I	*P*-value	Hypothesis*
2013/14			
1 (E2SFCA)	0.13386	<0.001	alternative
2 (E800)	0.05961	<0.001	alternative
3 (E1600)	0.13318	<0.001	alternative
4 (E3000)	0.05645	<0.001	alternative

Table 6.7: Residual autocorrelation from non-spatial models … continued			
5 (N800)	0.13730	<0.001	alternative
6 (N1600)	0.13359	<0.001	alternative
7 (N3000)	0.13559	<0.001	alternative
2014/15			
1 (E2SFCA)	0.01145	0.05	alternative
2 (E800)	0.09487	<0.001	alternative
3 (E1600)	0.08713	<0.001	alternative
4 (E3000)	0.04665	<0.001	alternative
5 (N800)	0.10127	<0.001	alternative
6 (N1600)	0.09558	<0.001	alternative
7 (N3000)	0.08327	<0.001	alternative
2015/16			
1 (E2SFCA)	0.01119	0.05	alternative
2 (E800)	0.09660	<0.001	alternative
3 (E1600)	0.08938	<0.001	alternative
4 (E3000)	0.02612	<0.001	alternative
5 (N800)	0.09954	<0.001	alternative
6 (N1600)	0.08996	<0.001	alternative
7 (N3000)	0.08875	<0.001	alternative
2013/16			
1 (E2SFCA)	0.108550	<0.001	alternative
2 (E800)	0.089708	<0.001	alternative
3 (E1600)	0.095201	<0.001	alternative
4 (E3000)	0.113270	<0.001	alternative
5 (N800)	0.096189	<0.001	alternative
6 (N1600)	0.088619	<0.001	alternative
7 (N3000)	0.096360	<0.001	alternative

*Alternative hypothesis is greater for all models (null hypothesis is random pattern)

Taking the above results into consideration is important to ensure an appropriate regression model, which is capable of incorporating the spatial component of the data, is selected. Thus for this analysis, as with previous analysis, a Bayesian approach, using a CAR prior, was chosen to model spatial data by adding a set of random effects to the model. Ecological regression models were then fitted for the same variables as non-spatial models. Results are presented as median values with 95% Credible Intervals (CI). The CIs indicate a 95% probability that the true parameter is in this range and, on average, it is that given as the median posterior. Additionally, if the CIs do not include 1 then a parameter within the given range is significant and can be estimated with certainty, as indicated in bold within the following tables of results. For Geweke diagnostics on model fit refer to Appendix E.

The first spatial regression model examined associations between environmental exposures and the risk of high weight status in children using the E2SFCA method of assessing spatial accessibility. It showed a weak but significant negative association between dairy/convenience, fruit/vegetable, and activity facilities and the risk of high weight status (Table 6.8). This indicates that areas with higher accessibility of dairy/convenience, fruit/vegetable, and activity facilities have a protective effect on the risk of high childhood weight status. This was particularly true of fruit/vegetable and activity facilities where a one unit increase in the E2SFCA measure of these exposures corresponded to a 7.151% and 4.972% decrease in risk respectively (Table 6.8). Thus, it can be concluded that using the E2SFCA model of exposure accessibility decreased risk of high weight status in children is related, at an ecological level, to increased accessibility of dairy/convenience, fruit/vegetable, and activity facilities.

Table 6.8: *E2FCA-based model*

	Median	2.5% CI	97.5% CI
Model 1 – E2SFCA			
Intercept	2.50653	2.40368	2.61536
Fast Food	1.00864	0.99134	1.02665
Takeaway	0.98847	0.96870	1.00743
Dairy/Convenience	**0.97844**	**0.95849**	**0.99900**
Supermarket	0.99025	0.96870	1.01228
Fruit/Vegetable	**0.92849**	**0.90565**	**0.95256**
Activity Facilities	**0.95028**	**0.93156**	**0.96860**

The second, third, and fourth models examined associations between environmental exposures and the risk of high weight status in children using Euclidean-based buffers of 800, 1600m, and 3000m respectively as measures of assessing spatial accessibility. Model 2 shows a weak but significant positive association between public greenspace and the risk of high weight status as well as a significant, but weak, negative association between dairy/convenience, fruit/vegetable, activity facilities and the risk of high weight status (Table 6.9). This indicates that areas with higher accessibility of public greenspace are slightly more likely to have an increased risk of high childhood weight status whereas areas with higher accessibility of dairy/convenience, fruit/vegetable and activity facilities demonstrated a protective effect. This was particularly true of activity facilities where a one unit increase in this exposure category corresponded to a 4.276% decrease in relative risk (Table 6.9). In addition, Model 3 shows a weak but significant positive spatial association between fast food, public greenspace and the risk of high weight status as well as a significant but weak negative association between takeaway, dairy/convenience, fruit/vegetable, activity facilities and the risk of high weight status (Table 6.9). This indicates that, given this measure, areas with higher accessibility of fast food and public greenspace are slightly more likely to have an increased risk of high childhood weight status whereas areas with higher accessibility of takeaway, dairy/convenience, fruit/vegetable, and activity facilities demonstrated a protective effect. Furthermore, Model 4 demonstrates a weak but significant positive association between public greenspace and the risk of high weight status as well as a significant but weak negative association between fast food, takeaway, dairy/convenience, fruit/vegetable, and activity facilities and the risk of high weight status (Table 6.9). This indicates that areas with higher accessibility of public greenspace are slightly more likely to have increased risk of high weight status whereas areas with higher accessibility of fast food, takeaway, dairy/convenience, fruit/vegetable, and activity facilities demonstrated a protective effect on the risk of high weight status in children.

Table 6.9: *Euclidean-based buffer models*

	Median	2.5% CI	97.5% CI
Model 2 – E800			
Intercept	2.11425	2.02182	2.21068
Fast Food	0.99392	0.98600	1.00180
Takeaway	0.99920	0.99571	1.00260
Dairy/Convenience	**0.98167**	**0.97590**	**0.98768**
Supermarket	0.98847	0.97434	1.00250
Fruit/Vegetable	**0.97190**	**0.94895**	**0.99471**
Activity Facilities	**0.95724**	**0.94971**	**0.96493**

Table 6.9: *Euclidean-based buffer models … continued*			
Greenspace – Private	0.99920	0.99790	1.00050
Greenspace – Public	**1.00015**	**1.00010**	**1.00020**
Model 3 – E1600			
Intercept	2.35137	2.21865	2.49029
Fast Food	**1.00682**	**1.00200**	**1.01167**
Takeaway	**0.99770**	**0.99591**	**0.99950**
Dairy/Convenience	**0.99154**	**0.98876**	**0.99422**
Supermarket	0.99283	0.98403	1.00190
Fruit/Vegetable	**0.98570**	**0.97297**	**0.99830**
Activity Facilities	**0.97580**	**0.97190**	**0.97981**
Greenspace – Private	0.99980	0.99800	1.00170
Greenspace – Public	1.00301	0.99700	1.01216
Model 4 – E3000			
Intercept	2.32612	2.25354	2.40152
Fast Food	**0.98108**	**0.97941**	**0.98265**
Takeaway	**0.99461**	**0.99412**	**0.99511**
Dairy/Convenience	**0.99710**	**0.99591**	**0.99820**
Supermarket	0.99780	0.99233	1.00341
Fruit/Vegetable	**0.98413**	**0.97551**	**0.99302**
Activity Facilities	**0.98847**	**0.98649**	**0.99035**
Greenspace – Private	0.99800	0.99551	1.00050
Greenspace – Public	1.00010	0.99860	1.00170

Thus, it can be concluded that using Euclidean-based buffer models of exposure accessibility decreased risk of high weight status in 4 – 5 year old children is related, at an ecological level, to increased accessibility of dairy/convenience, fruit/vegetable, and activity facilities. This also extended to takeaway outlets for the larger two buffer sizes of 1600m (Model 3) and 3000m (Model 4) but not for the smallest buffer of 800m (Model 2), and overall demonstrated minor associations. Increased risk was related to fewer exposure categories, none of which were consistently observed.

In addition, the fifth, sixth, and seventh models examined associations between environmental exposures and the risk of high weight status in children using Network-based buffers of 800, 1600m, and 3000m respectively as measures of assessing spatial accessibility. Model 5 shows a weak but significant positive association between public greenspace and the risk of high weight status as well as a significant but weak association between dairy/convenience, activity facilities and the risk of high weight status (Table 6.10). This indicates that areas with higher accessibility of public greenspace are slightly more likely to have an increased risk of high childhood weight status whereas areas with higher accessibility of dairy/convenience and activity facilities demonstrated a protective effect. This was particularly true of activity facilities, where a one unit increase in this exposure corresponded to a 5.096% decrease in risk (Table 6.10). Additionally, Model 6 demonstrates a significant but weak negative association between dairy/convenience, activity facilities and the risk of high weight status.

This indicates that areas with higher accessibility of dairy/convenience and activity facilities have a protective effect on the risk of high weight status in 4 – 5 year old children. No exposure categories exhibited positive associations for this model. Furthermore, Model 7 shows a weak but significant negative association between fast food, takeaway, dairy/convenience, fruit/vegetable, activity facilities and greenspace, both private and public, and the risk of high weight status (Table 6.10). Supermarket was the only category which did not exhibit significant effects, given this model. This indicates that the former categories demonstrate a protective effect on the risk of high weight status, although the results indicate only minor associations (Table 6.10).

Table 6.10: *Network-based buffer models*

	Median	2.5% CI	97.5% CI
Model 5 – N800			
Intercept	2.01375	1.94410	2.08694
Fast Food	0.98778	0.97590	1.00010
Takeaway	0.99760	0.99233	1.00270
Dairy/Convenience	**0.97287**	**0.96416**	**0.98147**
Supermarket	0.98147	0.96165	1.00180
Fruit/Vegetable	0.98590	0.95142	1.02337
Activity Facilities	**0.94904**	**0.93669**	**0.96146**
Greenspace – Private	0.99900	0.99780	1.00030
Greenspace – Public	**1.00351**	**1.00260**	**1.00441**

Table 6.10: *Network-based buffer models … continued*			
Model 6 – N1600			
Intercept	2.16517	2.06907	2.23653
Fast Food	1.00501	0.99900	1.01116
Takeaway	0.99900	0.99651	1.00130
Dairy/Convenience	**0.98491**	**0.98089**	**0.98896**
Supermarket	0.99025	0.97883	1.00160
Fruit/Vegetable	0.98896	0.97083	1.00713
Activity Facilities	**0.96802**	**0.96252**	**0.97346**
Greenspace – Private	0.99960	0.99800	1.00110
Greenspace – Public	1.00401	0.99800	1.01215
Model 7 – N3000			
Intercept	2.17646	2.11171	2.24319
Fast Food	**0.97795**	**0.97580**	**0.98000**
Takeaway	**0.99243**	**0.99173**	**0.99312**
Dairy/Convenience	**0.99481**	**0.99322**	**0.99641**
Supermarket	0.99461	0.98748	1.00190
Fruit/Vegetable	**0.98541**	**0.97502**	**0.99960**
Activity Facilities	**0.98442**	**0.98177**	**0.98708**
Greenspace – Private	**0.99880**	**0.99780**	**0.99970**
Greenspace – Public	**0.99720**	**0.99491**	**0.99950**

Thus, it can be concluded that using the Network-based buffer models of exposure accessibility decreased risk of high weight status in 4 – 5 year old children is related, at an ecological level, to increased accessibility of dairy/convenience stores and activity facilities. This also extended to other exposure categories for the largest buffer of 3000m (Model 7), however as noted these associations were minor. Increased risk was related to public greenspace within the 800m buffer only (Model 5), this was not consistently observed.

Overall, supermarket was the only category which did not show significant results for any of the buffer models, both Euclidean and Network-based. Conversely, dairy/convenience and activity facilities were the only exposure categories to show significant result for all seven spatial models, consistently showing a protective effect on the risk of high weight status in children. This was more pronounced for activity facilities than dairy/convenience in all models. Fruit/vegetable was also shown to have a protective effect on the risk of high weight status for all models, however, this was not significant for the 800m and 1600m buffers Network-based buffers (Models 5 and 6 respectively). The takeaway category, while showing a very minor protective effect, was significant in less than half of the models and demonstrated inconsistent results overall. Additionally, fast food showed mixed results and was not significant for many of the spatial models, this category was the least consistent. Results for greenspace measures were also mixed and in many cases not significant. To conclude, the E2SFCA model showed the strongest results, particularly for fruit/vegetable and activity facilities categories. Generally, weak results were consistent throughout all buffers, although some are significant.

6.5 Discussion

Of particular interest are results of the z-score comparisons where New Zealand children are shown to be only slightly taller but significantly heavier than the global standard population given by the WHO. It also shows that New Zealand children have substantially higher BMI when compared to the standard population. This is reflective of earlier research (Rajput et al., 2015), and raises concern over the weight status of New Zealand children. When looking into these results further to focus on demographic patterns, the most distinct results were those regarding ethnicity. Of children living in urban areas those of Māori and Pacific ethnicities were far more likely to be of high weight status compared to those of European/Other ethnic groups. The high weight status and number of children in this ethnic group category may contribute to the higher weight-for-age and BMI-for-age z-scores that were seen overall. As with T2DM (Chapter 5), high weight status within these ethnic groups may be due to their relatively rapid acculturation. This has led to significant changes in dietary composition which have not been adequately matched by the body’s metabolic pathways (Scobie & Samaras, 2014). These are notable findings which clearly distinguish high risk population groups and may, in turn, help to target and tailor prevention efforts. It is important to note, however, that the BMI classification used may be ill-suited to all ethnic groups due to difference biological and genetic factors, and research has suggested that ethnic-specific classifications or a system based on waist circumference measurement may be more accurate (Seidell, 2000).

As the primary focus of this thesis is on spatial patterning and associations, it is notable that only a small percentage of Data Zones (< 2% for each year) had no 4 – 5 year old population at all while some Data Zones had only a small amount population of 4 – 5 year old children, all of which were of high weight status and resulted in crude rates of 1,000 per 1,000. While this can still be considered within analysis, it should be noted that had the data been for a more varied age group of children, and a subsequently larger population group overall, results may have differed. There was also a relatively high standard deviation and many outliers for each year, indicating that data values are fairly dispersed and do not necessarily cluster around the mean. These trends were fairly consistent for all years considered.

Overall, high weight status was inconsistently dispersed throughout urban New Zealand and there was little distinct spatial patterning of crude rates per 1,000 and SMR, with all urban areas showing a mix of low, moderate, and high rates for all years considered. Southern areas of Auckland did demonstrate some concentrations of higher rates per 1,000 however these were inconsistently observed. Additionally, while global clustering showed significant high clusters local clustering results differed. Although demonstrating some significant hot and cold spots, results from local clustering showed inconsistent spatial patterns overall. Notable exceptions were that southern Auckland demonstrated higher concentrations of hot spots and the spatial pattern was more consistent here than other urban areas, for all years. Also, while Whangarei showed concentrations of hotspots, this was most pronounced for 2014/15 and less consistent when considering other years. Furthermore, global autocorrelation results were stronger for crude rate per 1,000 than SMR, demonstrating that taking into account the ethnic composition of an area may be an important factor when considering spatial aspects of health outcomes. Local autocorrelation however, much like clustering results, demonstrates a fairly random spatial pattern and does little to identify particular concentrations of high or low clustering or outliers. The above provides valuable insight by highlighting the lack of consistent geographic areas of high or low risk, thus providing information on the diverse nature of spatial distribution patterns of high weight status in 4 – 5 year old children within urban New Zealand. Overall, this health concern appears to be fairly randomly distributed which may be reflective of this specific population group as a whole.

Results also demonstrate autocorrelation of residuals within standard GLM regression models, substantiating the need for an appropriate regression model which can account for spatial relationships. These spatial relationships are integrated into analysis by using a

Bayesian approach to regression analysis. Subsequent results of this demonstrate some interesting associations, although these were generally weak.

Overall, the environmental exposures which are deemed as unhealthy, including fast food, takeaway, and dairy/convenience stores (refer to Chapter 4 for further detail), showed mixed results. Fast food demonstrated significance for only some of the models, the direction of which was inconsistent. Additionally, the takeaway category demonstrated a slightly protective effect however this was very weak and was only significant for half of the regression models. Conversely, dairy/convenience was one of the few categories to show significance for all regression models, demonstrating a slightly protective effect on the risk of high weight status in children. Again, these associations were very weak. While previous research has demonstrated that such unfavourable types of stores and outlets have been associated with negative health outcomes including increased incidence of high weight status in children (Carroll-Scott et al., 2013; Chen & Wang, 2016b; Fraser & Edwards, 2010; Grafova, 2008; Hamano et al. 2017; Newman, Howlett & Burton, 2014; Pearce, Bray & Horswell, 2018), this was not supported by the current results. They do, however, align with other research which has also found mixed or null associations between high weight status in children and exposures related to such aspects of the food environment (Berge et al., 2014; Casey et al., 2012; Cetateanu & Jones, 2014, Choo et al., 2017; Corrêa et al., 2018; Ghendanik et al., 2018; Griffiths et al., 2014; Koiletat et al., 2012; Lakes & Burkart, 2016). Such variations in results may be reflective on many aspects including, but not limited to, differential zoning regulations and proliferation of these exposures within differing contexts. They may also reflect differing definitions of the exposure itself (refer to Chapter 2 and Appendix A.3), and what sub-categories are included in such categorisations.

Regarding environmental exposures considered as healthy, including supermarkets, fruit/vegetable stores, greenspace, and activity facilities (refer to Chapter 4 for further detail), many results demonstrated fairly consistent significance. Interestingly, supermarkets were the only environmental exposure category which did not show significance for any regression model. This is contrary to international research which has suggested that density and proximity of supermarkets can have positive effects on health outcomes including obesity and body weight (Carroll-Scott et al., 2013; Chen & Wang, 2016b; Grafova, 2008; Larsen et al., 2015; Liu, Wilson, Qi & Ying, 2007). Such research has predominately been conducted within North America, however, which has a relatively distinct spatial patterning of built environment exposures relative to the New Zealand context. Additionally, given the expansive range of products offered, and the lack of data on food purchasing, the fact that supermarkets offer healthy products does not mean that they are being purchased and subsequently consumed by children and/or their parent or guardian. It is also important to consider that supermarkets offer a substantial range of unhealthy products, particularly pre-packaged foods which are high in refined sugars which may, in part, contribute to mixed results. The fruit/vegetable exposure category, however, showed significance for the majority of regression models, demonstrating a protective effect on the risk of high weight status in children. Veugelers, Sithole, Zhang and Muhajarine (2008) found similar results in their study on Canadian children, however, other research has largely shown mixed results when considering the influence of accessibility to fruit and vegetable retailers (Corrêa et al., 2018, Koiletat et al., 2012). This may, in part, be due to the purchasing power of parents and guardians and the fact that such stores often tend to locate on the fringes of urban areas, relative to other exposures, and therefore may not be accessible to those living in the densest areas of large cities.

Additionally, activity facilities (refer back to Chapter 4, Section 4.3.1 for details of included sub-categories) was the second of two environmental exposure categories to show significance for all regression models, the other was dairy/convenience as noted earlier. An increase in activity facilities was shown to consistently have a protective effect on childhood weight status for all models. This relationship is also evident within the literature with studies by Gilliland et al. (2012), Veugelers et al. (2008), Slater et al. (2010), and Wolch et al. (2011) finding similar results. While an interesting finding, this does not unequivocally prove that having increased accessibility to activity facilities leads to a reduction in body weight but it may reflect the propensity for children and families to exercise, both outdoors and indoors, if facilities are more available. Finally, greenspace demonstrated inconsistent results, whereby private greenspace only reached significance for one model (Model 7), showing a very minor protective effect while public greenspace reached significance for half of the regression models but showed inconsistent directions of association, again with very weak results.

Previous research relating to greenspace accessibility and health outcomes of T2DM and weight status have shown varied results, with some finding relationships in the expected direction (Bell, Wilson & Liu, 2008; Liu et al., 2007; Schalkwijk et al., 2018), and others finding no significant relationships (Choo et al., 2017, Lakes & Burkart, 2016; Gose et al., 2017; Potestio et al., 2009). Such research has, however, done little in regard to sub-grouping greenspace into public and private sub-categories so direct comparisons with the results of this study are not possible. Furthermore, greenspace may be differentially utilised based on aesthetic quality, cleanliness, and safety which are important considerations.

Much like the current study, a large body of research has demonstrated mixed or inconclusive results when analysing associations between the built environment and high weight status in children (see Chapter 2, Section 2.3 and Appendix A.3 for further details). Much of this research has, however, been based solely on administrative areas such as census tracts (Cetateanu & Jones, 2014; Chen & Wang 2016b; Edwards et al., 2010; Grafova, 2008; Howard Wilsher et al., 2016; Hughey et al., 2017; Jenkin, Pearson, Bentham, Day & Kingham, 2015; Koleilat et al., 2012; Lakes & Burkart, 2016; Newman et al., 2014; Potestio et al., 2009; Saelens et al., 2012; Schalkwijk et al., 2018; Shier & Sturm, 2012; Slater et al., 2010). This does little to measure access beyond arbitrary boundaries and is susceptible to the Modifiable Areal Unit Problem (MAUP) and the Uncertain Geographic Context Problem (UGCoP – see Kwan, 2012), and may therefore misclassify relevant study areas. Other research has sought to address such issues of spatial restriction by constructing buffers, which can be either Euclidean or Network-based, in order to capture larger study areas which are potentially more relevant (Bell et al., 2008; Berge et al., 2014; Casey et al., 2012; Corrêa et al., 2018; Ghenadenik et al., 2018; Gilliland et al., 2012; Gose et al., 2013; Hamano et al., 2017; Jennings et al., 2011; Jilcott et al., 2011b; Le, Engler-Stringer & Muhajarine, 2016; Pearce et al., 2018; Schwartz et al., 2011; Timperio et al., 2010; Wolch et al., 2011).

Some research has also sought to remove issues around boundary and edge effects caused by administrative units and buffers altogether by using metrics such as closest distance (Carroll-Scott et al., 2013; Choo et al., 2017; Fraser & Edwards, 2010; Griffiths et al., 2014; Larsen et al., 2015; Liu et al., 2007; Miller, Joyce, Carter & Yun, 2014; Oreskovic et al., 2009; Zhang et al., 2016). Such measures are often restricted to only considering the one exposure which is closest, however, and can therefore disregard associations with exposures at a further distance which may still be geographically accessible and of importance. To account for these concerns various buffer sizes, as well as the E2SFCA model measuring accessibility to the five closest of each environmental exposure, were used within this study. This provides not only a means of judging associations within different accessibility metrics but also serves as a means of sensitivity analysis to assess how results varied by the accessibility metric used. Overall, while much of the previous international research has found strong associations between unhealthy food retailers and body weight status the strongest results for this study were shown to be for the fruit/vegetable and activity facilities categories (refer to Appendix

A). While the current study did not find vast differences in results between buffers, of both Euclidean and Network design, it did show a difference in results when considering the E2SFCA. The results from this model, although following a similar pattern to those of buffers, demonstrated stronger associations for the exposures deemed significant. This emphasises the importance of including measures of spatial accessibility beyond administrative units and buffers alone which may provide a more suitable indication of spatial accessibility. These results concerning associations between exposures of the food and physical activity environments and high weight status in children are important considerations which both align and conflict with previous research, demonstrating the variability of the New Zealand context.

As with the previous chapter, results of this study should be interpreted with consideration of its limitations. Firstly, this study is ecological in nature and may be prone to issues regarding aggregation. Secondly, as this study is cross-sectional it can only provide a limited measure of spatial accessibility over a given time and may also be susceptible to issues of parental residential self-selection. When considering the current body of literature which looks at associations between the built environment and high weight status, the majority of studies focus on adult populations. Studies with a focus on children constituted only 29.3% of all studies considering body weight status within the earlier literature review, the majority of which also used a cross-sectional study design (refer to Chapter 2, Section 2.3). Focusing on children within a specific age group may be limiting, however, as this population have little purchasing power or individual control over food consumption and activity opportunities. Additionally, as noted earlier, while the rationale for using BMI classifications is warranted it may distort results for particular ethnic groups. This is because particular ethnic groups may have unique body compositions (Seidell, 2000), and therefore the same standard may not be best applied to every ethnic group.

Furthermore, there are many factors besides spatial proximity that should be taken into account when trying to assess how populations access environmental exposures such as quality and cost of products and services. In fitting with this, food knowledge of children's parents or caregivers is another important factor to consider as this is likely to influence purchasing and consumption patterns. Campbell (2016) has highlighted the importance of considering the influence of a child's home and family environment which is, in turn, embedded within the larger context of the wider societal environment. Finally, not only do populations regularly access food and areas for physical activity outside of their direct neighbourhood, but their perception of neighbourhood may differ from the measures used in this study. Thus, longitudinal studies and further assessment of the influence of quality, cost, food knowledge, mobility patterns, and the patterns of parent or caregiver dietary and physical activity is needed to fully understand relationships discussed within this study.

6.6 Chapter summary

In conclusion, this chapter contributes to an international body of research which focuses on the spatial distributions of high weight status in children and ecological associations with both the food and physical activity environments. The purpose of this chapter was to address Objective 3 and 4 (see Chapter 1, Section 1.3.1 on 'aims and objectives'), by investigating the spatial distribution of high weight status in children throughout urban New Zealand and examining potential associations with built environment exposures. Previous research has largely focused on the use of administrative areas and buffers as a means of assessing spatial accessibility. As with the previous analytical chapter, this chapter has advanced on this by also considering an alternative measure using an E2SFCA model. Additionally, it has used a national level dataset to assess high weight status in 4 – 5 year old children and has focused on the spatial aspects of this data. It has also considered all urban areas of New Zealand rather than focusing on a specific city or isolated geographic area, thus offering a comprehensive view of this health concern. In doing so, this chapter has demonstrated distinct demographic patterning of high weight status in children and some interesting associations with the built environment. It has also shown the complex and inconsistent spatial patterning of this health issue. While these results do not offer unequivocal evidence that certain aspects of the built environment may have a detrimental or protective effect on weight status in children they do demonstrate some significant demographic and environmental relationships which warrant further attention.

Chapter 7 : The built environment and chronic health conditions in urban New Zealand: A discussion

7.1 Preface

The preceding three analytical chapters presented and discussed results of the environmental exposures used within this study and their relationship with socioeconomic deprivation (Chapter 4), as well as the spatial distribution of both T2DM and high weight status in 4 – 5 year old children and potential associations between these health outcomes and environmental exposures (Chapters 5 and 6 respectively). The purpose of the current chapter is to discuss the overall themes that emerged from these results and position them within the context of existing literature.

This chapter specifically addresses Objective 5, which is to evaluate the overall themes of this thesis and discuss a geospatial understanding of relationships between the built environment and health (see Chapter 1, Section 1.3.1 on 'aims and objectives'). In doing so, this chapter aims to provide a more holistic discussion of these themes rather than going into detail about specific relationships relevant to one topic, as these are already addressed within previous chapters. This chapter consists of three main sections: (1) discussing chronic health conditions in urban New Zealand with regard to the topics of this thesis and providing a geospatial perspective (Section 7.2); (2) discussion of policy which is relevant to the findings and overall themes (Section 7.3); and (3) discussing the limitations of the current study (Section 7.4). It will then conclude by providing a short chapter summary.

7.2 Chronic health conditions in urban New Zealand

This section discusses the chronic health conditions considered within this thesis, T2DM and high weight status in 4 – 5 year old children. It provides a short discussion of the overall demographic patterns for these health issues and the influence of the socioeconomic context and economic accessibility before addressing them within a geospatial context. As noted earlier, the purpose of this chapter is not to reiterate results and discussion from previous chapters, but rather to provide a discussion which considers these chronic health conditions within urban New Zealand as a whole.

7.2.1 Demographic patterns and economic accessibility

As this thesis focuses on a specific group of children, aged 4 – 5 years old, for high weight status and the overall urban population for T2DM it is notable that demographic patterns regarding age will only apply to the latter. As these have been discussed within the relevant chapter (Chapter 5), they will not be reiterated here. What is important to note, however, is that the results found for the former of these health issues, high weight status in children, are for the 4 – 5 year old age group only and may differ if considering children of a different age group or children overall. National results from the New Zealand Health Survey (NZHS) do however demonstrate similar results for children of a wider age range (Ministry of Health, 2016b). Interestingly, males were more likely than females to be of high weight status during early childhood as well as have T2DM in later life. While a link cannot be made between the T2DM and childhood weight status datasets or, at a larger scale, these two health issues in general this may provide some evidence of demographic patterns related to chronic health conditions. It may also provide an opportunity for further research to look more closely at the dietary, activity and treatment seeking behaviours of different genders, at various ages, to understand if there are any distinct variations in risk factors.

The most prominent demographic pattern however is that regarding ethnicity. For both health conditions there were a significant number of people identifying as European/Other ethnicities affected, however, those of Māori and Pacific ethnicities had a significantly higher proportion of people affected. This is consistent with health outcomes for these ethnic groups found in previous research (Ministry of Health, 2016b; Rajput et al., 2015; Sundborn et al., 2007). Those identifying as Māori were shown to be approximately twice as likely to have either T2DM or high weight status in childhood compared to those of European/Other ethnicity. This was even more pronounced for those of Pacific ethnicities who were three times as likely to have either T2DM or high weight status in childhood compared to those of European/Other ethnicity. These results are largely reflective of the majority of non-communicable and chronic health conditions within New Zealand, where Māori and Pacific Peoples have been shown to have significantly poorer health outcomes than other ethnic groups (Ministry of Health, 2016b). As discussed previously, this may be due to relatively rapid acculturation of indigenous and minority ethnic groups. Such acculturation has led to significant changes in the dietary composition of these groups which has not been adequately matched by the body's metabolic pathways, thus resulting in a higher susceptibility of developing chronic health conditions such as obesity and T2DM (IDF, 2015; Scobie &

Samaras, 2014). Results of this study may also be influenced by the fact that there are higher proportions of Pacific People living within urban areas, so they may be slightly over-represented within this study. Additionally, such ethnic groups are disproportionately located within deprived areas of urban New Zealand which have been shown to have a negative influence on health and overall poorer health outcomes (Feng et al., 2010; Ministry of Health, 2016b; Schneider et al., 2015). This raises the important issue of economic accessibility.

Research from New Zealand has found that all environmental exposures cluster within deprived areas (Pearce et al., 2008a; Sushil et al., 2017; Wiki, Kingham & Campbell, 2018). This suggests that people living in deprived areas have greater access to food retailers and areas for activity. Not all food products and activity options are equally priced however and while there may be increased spatial access this does not necessarily equate to increased economic access. Therefore, even when living in closer proximity to food outlets those with limited financial means may not necessarily have access to health-promoting resources which are costly. For example, while locating a sports facility in a deprived area may be a financially beneficial option for business owners, as they will pay lower land rental costs, this does not mean that those living in the area will necessarily have the financial means to join such facilities which generally have membership fees (Rabiee, Robbins & Khan, 2015; Withall, Jago & Fox, 2011). Additionally, open spaces for recreation and physical activity which are free of cost may be underused due to safety concerns or the quality of the space.

Furthermore, the significant amount of energy-dense and nutrient-poor foods, which are typically lower in cost, sold within retail stores may impact on purchasing behaviour and subsequent food consumption. Lowe et al. (2009) have provided evidence that the human body exhibits good physiological defences against energy depletion; however, defences are weak against excess energy accumulation. This is particularly true when highly palatable food opportunities are abundant, as they have been shown to be within deprived areas of urban New Zealand (Wiki et al., 2018). These factors may contribute to lower physical activity levels and poorer dietary habits of populations living in socioeconomically deprived areas, reflecting the amplification of vulnerability. Overall, while the datasets on T2DM and childhood weight status cannot be linked, and the relationship between these health conditions cannot unequivocally be proven here, demographic trends can be observed which are indicative of chronic health conditions within New Zealand and internationally (Ministry of Health, 2016b; WHO, 2014). These are notable findings as they clearly distinguish high risk population groups which may, in turn, help to target and tailor prevention efforts.

7.2.2 A geospatial understanding

While demographic factors and economic accessibility undoubtedly have an important influence on health outcomes of T2DM and the weight status of children, the main focus of this research is on spatial determinants. Therefore, this section will discuss spatial distributions and spatial accessibility in turn. Again, as these are discussed in detail within the relevant chapters (Chapter 5 and 6) this is not intended to be an exhaustive discussion, but rather a brief and holistic discussion regarding the spatial nature of these health outcomes within urban New Zealand.

7.2.2.1 Spatial distributions

Examining the spatial distribution of T2DM and high weight status in 4 – 5 year old children results showed that all urban areas had variation in these health outcomes. This included having both low and high rates and SMR as well as hot and cold spots for clustering. This was, however, more pronounced for high weight status in children whereby all urban areas demonstrated little distinct spatial patterning for this health outcome. In contrast, results for T2DM did show some variation, particularly within smaller urban areas, and there were notable areas which demonstrated clusters of high rates and SMR, predominantly within the south and west of the Auckland region. Such areas also showed similar results for high weight status in children, although these were much less pronounced. In some respect these findings are expected as these areas are largely of low socioeconomic status and contain significant populations of Māori and Pacific Peoples which are prominent risk factors, as previously discussed. Overall, spatial distributions of high weight status in children and T2DM were dissimilar. This was primarily due to the lack of distinct patterning within the results for high weight status in children. Future research may benefit from comparing these areas spatially with regard to high weight status in adults, rather than children. This is because T2DM generally occurs in later stages of life and thus may be more influenced by, and reflective of, health concerns regarding weight status of the adult population.

7.2.2.2 Spatial accessibility

Another important theme and focus of this thesis is that of spatial accessibility and the association with chronic health outcomes. Spatial accessibility in this context is a measure of how accessible certain environmental exposures are depending on their spatial and geographical proximity to urban neighbourhoods. Various environmental exposures were investigated including those which can be considered as health promoting such as greenspace, physical activity facilities, fruit and vegetable stores, and supermarkets as well as those considered to be detrimental to health such as fast food, takeaways, and dairy/convenience stores. For both health outcomes, T2DM and high weight status in children, results showed variable effects of these environmental exposures.

The most notable and consistent results were those for physical activity facilities and fruit and vegetable stores which were shown to have a protective effect on the risk of both high weight status in children and T2DM. While this aligns with some previous research (Christine et al., 2015; Li & Lopez, 2016), it is also contrary to other research which has found mixed or null results for these exposure categories (Barrientos-Gutierrez et al., 2017; Casey et al., 2012). Results for environmental exposures considered to be detrimental to health were less consistent and often lacked statistical significance. This was, however, also true of greenspace and supermarkets. This is contrary to previous research which has found significant relationships between such detrimental resources and poorer health outcomes (Bodicoat et al., 2015; Carroll-Scott et al., 2013; Fraser & Edwards, 2010; Gebreab et al., 2017; Hamano et al. 2017; Mezuk et al., 2016), as discussed in further detail within the chapters 5 and 6. Results of this study may differ from such research because of the unique New Zealand context and the fact that many previous studies have considered isolated exposures. Additionally, such associations may also be reflective of residential self-selection for those of high socioeconomic status whereby populations with an interest in maintaining a healthy lifestyle locate themselves nearer to facilities and opportunities by which to maintain such a lifestyle (Lake & Townshend, 2006). These population groups may also have the economic means by which to patronise facilities requiring paid membership or retailers selling healthier foods, generally at a higher cost. Overall, spatial modelling of accessibility and its relationship with the chronic health conditions considered within this study demonstrated that access to health promoting resources may be more influential than access to resources which are generally considered to be detrimental to health. Interestingly, this relationship was consistent even when investigating different health outcomes, T2DM and high weight status, and different population groups, both the whole urban population and children specifically. It is important, however, to consider what exposures are included and how these are modelled as well as the interconnection between spatial, economic and sociocultural accessibility.

There are also some notable factors which should be considered within any statistical and spatial analysis to ensure that results are interpreted correctly and with caution. Firstly, as this is an exploratory analysis it does not set out to test pre-defined hypotheses for much of the spatial analysis. Instead, it is open to observing spatial patterns and associations as they may arise or become evident. Additionally, ecological analyses such as the approach taken within this research are often limited by the nature of this approach. For example, the use of administrative units may be ill-suited to examine associations between the built environment and health outcomes. Such units are subject to the modifiable areal unit problem (MAUP) and the Uncertain Geographic Context Problem (UGCoP – see Kwan, 2012) and therefore may misclassify relevant study areas. Such ecological research is also limited in the respect that it cannot make conclusions regarding individuals based on observations of aggregated data; this is referred to as the ecological fallacy (Winzar, 2015). It is important, however, to bear in mind that the absence of evidence within this or any other analyses does not necessarily equate to the notion that there is an absolute absence of any relationship or association. It may instead indicate that there are further factors which need to be considered in order to have a complete understanding of the relationships discussed.

Furthermore, while certain methods and models may be commonly used and understood, analyses should not be limited to these alone and should instead seek to find the best methods, models, and means of understanding the data and associations within the given context. As eloquently noted by the prominent statistician Sir Ronald Fisher, “no scientific worker has a fixed level of significance at which from year to year, and under all circumstances, he rejects hypotheses; he rather gives his mind to each particular case in the light of his evidence and his ideas [sic]” (Fisher, 1973, p44-45). Finally, while spatial and statistical models are increasingly helping to understand and predict associations it is important to note that a model alone should never be confused with the complexities of the underlying realities than it intends to model. Consideration should also be given to theories and models which aim to include various aspects, such as a complex systems approach.

Again, while the datasets on T2DM and childhood weight status cannot be linked, and the relationship between these health conditions and environmental exposures cannot be unequivocally proven, there are spatial trends which can be observed. These are reflective of previously reported spatial distribution trends of such health conditions, both within New Zealand and internationally (Ministry of Health, 2015; Ministry of Health, 2016b; WHO, 2014). They also offer an insight into the influence of environmental exposures on such health conditions and demonstrate that despite the intuitive appeal behind restricting access to exposures considered as detrimental to health it may be as effective, if not more so, to increase access both economically and spatially to exposures which are health promoting.

7.3 Policy

The above are notable findings as they distinguish areas which may be influential on population health outcomes and, in turn, aid in the development of planning and policy initiatives directed toward reductions in, and prevention of, chronic health conditions. Swinburn et al. (2011) have stated that "no country can act as a public health exemplar for the reduction of obesity and Type 2 Diabetes" (p804). There are, however, many frameworks and policies in place both internationally and within New Zealand which are aimed at reducing non-communicable health conditions such as T2DM and obesity.

Internationally, for example, the International Diabetes Federation (IDF, 2015) has multiple frameworks and tools which are directed towards an overall reduction in T2DM including a framework on action for sugar, a diabetes prevention score, and a global diabetes scorecard. The former of these is aimed at a reduction in sugar consumption as well as in increase in the availability and production of healthy food products. The latter two are focused on enabling cities to assess how urban environments can be improved in order to prevent T2DM as well as helping to improve public health accountability and track the progress of national governments in regard to diabetes care and prevention. The diabetes global scorecard details this by highlighting areas of good practice and identifying areas which can be improved upon. Through this, IDF (2015) found that a quarter of countries reported a lack of prevention policies focused on nutrition. Additionally, the diabetes prevention score has currently been tested in 32 countries worldwide, and while New Zealand has not yet applied this, neighbouring countries such as Australia have. Cities Changing Diabetes (CCD, 2015) also has a worldwide focus on diabetes in urban areas. Their research provides not only a multinational insight into the prevalence of diabetes in urban areas, but also possible environmental risk factors and how these may differ by country. It provides a valuable holistic viewpoint as well as some specific guidelines by which urban areas can address such health concerns and target prevention efforts. These may, in turn, provide critical steps in understanding and assessing how the urban environment in New Zealand is impacting T2DM outcomes.

Non-communicable health conditions are also a prominent focus within the United Nations Sustainable Development Goals (2015), which targets non-communicable diseases with many frameworks and policy options for assessing and preventing such health issues. For example, the United Nations provide access to the OneHealth Tool, which is software designed to strengthen health-system analysis using cost policy scenarios (WHO, 2014). In addition, the WHO provide many guidelines and tools which are aimed at non-communicable health conditions such as the STEPwise approach, used to monitor the national prevalence of raised blood glucose and obesity (WHO, 2014), the global strategy on diet, physical activity and health (WHO, 2004), and guidelines on sugars (WHO, 2015b). The Codex Alimentarius is also another instrumental tool which can be specifically used to understand and address food products and components such as fat, sugar, and salt (WHO, 2014).

While much of this is overarching in nature, there are places which have focused on more specific population groups such as children. An example of this is Canada where a ‘report card on healthy food environments and nutrition for children’ has been developed (Olstad, Raine & Nykiforuk, 2014). This aims to assess how children’s dietary behaviours and body weight status are supported or hindered by current environments and policies by assigning a grade to both policies and environments. By monitoring children’s food environments and relevant policies this tool can help to both inform stakeholders and governments as well as outline policy-relevant research agendas.

Many countries worldwide have also implemented taxes on certain products, dating back as early as 1981 in Norway (Mytton, Clarke & Rayner, 2012). Such taxes have been directed toward multiple products including: junk food and confectionary in Hungary, Finland, Mexico, French Polynesia, Nauru, and Australia; sugar and sugar sweetened beverages in France, Finland, Norway, Mexico, USA, Samoa, Fiji, Australia, French Polynesia, and Nauru; and saturated fat in Denmark (Mytton et al., 2012; WHO, 2014). There is argument that taxing such products is unpopular, however, and that a better approach may by to remove taxes from healthy food products such as fruit and vegetables and adequately label foods with nutritional information to educate the consumer instead. A notable example of the former is that fruit and vegetables attract no goods and services tax in Australia, whereas the applicable tax rate for such products in New Zealand is 15% (Swinburn et al., 2013). Additionally, considering the latter, in countries such as Ecuador and the United Kingdom a food labelling system based on a traffic light approach has been put in place to assess and label fat, salt, and sugar content using ‘lights’ to indicate if the item is high, moderate or low in these ingredients (Kedgley & NZPHC, 2007; Vandevijvere et al., 2015b).

New Zealand also has policies in place to ensure non-communicable health conditions are appropriately managed, including overarching strategies such as the Ministry of Health's Healthy Families NZ programme, which aims to unite community leadership to aid in efforts for better health outcomes, and the He Korowai Māori health strategy which acknowledges the holistic nature of Māori health within the health sector (Ministry of Health, 2017c). The latter seeks to incorporate not only the physical self of the individual but also whānau (family), spiritual health, and connectedness. There are also policies and programmes which have a more specific focus such as Green prescriptions, which include advice from a health professional directing the patient to be physically active as a part of their health management, Healthy Eating – Healthy Action: Oranga Kai – Oranga Pumau, Mission On, The New Zealand HeartSAFE initiative, and Fruit in Schools (Kedgley & NZPHC, 2007; Ministry of Health, 2015; Vandevijvere et al., 2015b). Additionally, many community-based initiatives such as the Ngati and Healthy project in the East Coast of the North Island have shown good results overall and provide context-specific insights (Coppell et al., 2009).

Much of the research from The International Network for Food and Obesity/NCD Research, Monitoring and Action Support (INFORMAS) has also been within this field. This group is a global network of researchers and organisations that have a vested interest in the public and has many New Zealand members. It aims to monitor and support actions from both the public and private sectors in order to create healthy food environments and reduce non-communicable health issues (Swinburn et al., 2013). In doing so, they have created a Government Healthy Food Environment Policy Index (Food- EPI), which has a 'policy' component with domains on specific aspects of food environments, and an 'infrastructure support' component with domains in order to strengthen systems and prevent non-communicable health conditions (Swinburn et al., 2013), among other initiatives.

While the policies and programmes detailed above are undoubtedly important, research has argued that a neoliberal framework effectively silos academic, political, and policy organisations. This does not translate into effective outcomes and therefore limits the extent to which it is useful, particularly for population level outcomes. Many researchers and initiatives have, in turn, drawn attention to the increasing importance of an integrated and multi-sector approach to policy in order to achieve the desired population level results (Goran et al., 2013; Swinburn et al., 2011; Whiting, Unwin & Roglic, 2010; WHO, 2014). This includes policies within sectors such as education, trade, media and marketing, urban planning and development, transport, and health. Investment in technological developments through the use of the internet and patient portals or smartphone applications which can aid in booking appointments, managing healthcare instructions and prescriptions, and seeking advice may also be advantageous (Sidawi & Deakin, 2013). In addition, WHO (2014) have stated that appropriate policies aimed at modifiable risk factors include those which address affordability of health promoting resources, accessibility, and implementation capacity as well as increase awareness regarding behavioural risk factors and de-normalise unhealthy behaviours and habits. The aetiology of NCDs, despite having some over-arching themes, does however have unique characteristics for each country and community based on social, economic, and cultural influences. It is therefore important that policies are adaptable to local environmental and cultural contexts.

Overall, environments which are conducive to healthy eating choices and discourage the consumption of processed food which are energy-dense and high in fats and sugars can be influential for population health outcomes (Swinburn et al., 2011). While many policy options are directed towards changes within the food industry this is, however, an important and influential industry in New Zealand. It accounts for a substantial portion of the national economy, approximately 25% of the total sales market, and employs around 17% of the workforce (Kedgley & NZPHC, 2007). Egger and Swinburn (1997) have, in turn, noted that large scale changes within the food industry may prove unpopular and perhaps even detrimental to the national economy. Smaller changes can be made that do not target particular retailers however such as an overall reduction of sugar in beverages or fat in the meat supply.

Additionally, rather than using legislation to restrict the density and proliferation of unhealthy food outlets, local authorities may choose to instead work with them to change the nature of the food provided (Public Health England [PHE], 2014). Other potential policy options include reducing overall portion sizes, improving food labelling, and reducing GST payable on healthy foods to subsidise and incentivise the purchasing of healthy food products (Goran et al., 2013; Mann et al., 2015; Scobie & Samaras, 2014). Regarding the latter, food prices have been shown to be influential in the purchasing and subsequent consumption of food products (Anekwe & Rahkovsky, 2014). Many people are restricted to buying energy-dense, processed foods as these are typically mass produced and therefore lower in price. If healthier food options were subsidised this may lead to an increase in the population who are able to afford these and a subsequent increase in the consumption of healthy food products, to the benefit of individuals health and ultimately the health care sector as a whole.

Preventative care need not focus on medical care and food products only, however, which can be costly and unpopular. It may be better implemented through quality education on nutrition and physical activity. Education can play a key role when it comes to empowering people with the skills to understand and manage their environments and health effectively. The IDF (2015) have, in turn, argued that greater public health education is needed to not only improve the understanding of chronic health conditions, but also to embed lifestyle changes. This can include supporting the provision of cooking and nutrition classes, education on budgeting, and digital or online educational tools such as games, websites, and social networks (Sidawi & Deakin, 2013). Additionally, marketing and advertising can also be an effective way to manage exposure to food products and influence social norms around food consumptions and behaviours. In New Zealand, an estimated 70% of food advertisements have been classified as being counter to improved nutrition and major food franchises spend in excess of $100 million NZD annually on marketing, which includes considerable sports sponsorship (Kedgley & NZPHC, 2007). For example, KFC have sponsored the ICC cricket world cup and Surf Life Saving NZ, Wendy's burger franchise has sponsored the Warriors rugby league team, and McDonalds have sponsored the X Factor television show as well as regularly sponsoring sporting events. Kelly and Swinburn (2015) have argued that such sponsorships promote the consumption of energy-dense foods sold by these franchises and promote exercise alone, rather than in combination with a healthy diet, as a means of preventing obesity and other chronic health conditions. This does not address both sides of the energy balance equation however and contributes to social norms around the consumption of unhealthy foods, which does little to promote sustainable healthy eating habits.

In conclusion, the WHO (2014) has argued for an investment into the reduction of risk factors and disease prevention, instead of an investment in treatment. Much research has also argued that policies and intervention programs are more effective by targeting not only individuals, but also the physical, economic, and socio-cultural environments that they live in which can, in turn, shape individual risk (Egger & Swinburn, 1997; Laraia et al., 2012; Mann et al., 2015; Warin et al., 2016). Disregarding such contextual influences, which are inevitably a part of people's everyday lives, can mean policy initiatives are at risk of being ineffective. Thus, understanding socio-spatial relationships in local environments has important implications for policy initiatives and ultimately health outcomes. Research in this field, such as that provided within this thesis, can provide a platform on which to develop effective strategies and policies.

7.4 Limitations

As discussed within previous chapters, results of this study should be interpreted with consideration of its limitations. As this study is of cross-sectional design and ecological in nature it can only provide a limited measure of spatial accessibility and health outcomes over a given time period and may be prone to issues of aggregation. Thus, this study lacks knowledge of how long people have been living in their current environment. Local environments that individuals have been exposed to over the course of their lifetime may be of equal or more importance than current environments (Pearce, Shortt, Rind & Mitchell, 2016). In addition, people, if they have the means to do so, may also choose to position themselves in neighbourhoods which are aligned with their personal values and behaviours. This is termed residential self-selection whereby residents choose the neighbourhood they live in based on how the community and environment may reflect and align with their own position, as discussed previously. Such relationships can only be factored into analysis if the data is available and the study design is longitudinal however, which is a limitation of much ecological research.

Furthermore, there are many factors besides spatial proximity that should be taken into account when trying to assess how and why populations access and utilise certain environmental exposures. These include the quality and cost of products and services, transport and mobility services and behaviours, social norms, and food knowledge. For example, transport may affect not only how people travel but also the distance they are willing or able to travel for both food and activity opportunities (Kerr et al., 2012; Yang & Diez-Roux, 2012). The food and physical activity environments may also not be geographically proximal to neighbourhoods or places of residence as many people are willing to travel further for preferred quality and price of food products. The same is true of facilities for physical activity, particularly given the club-style nature of some sporting opportunities. Moreover, food knowledge, social norms, and economic viability may affect where people choose to visit and what they choose to purchase. These are all influential factors and play an important role in people’s decision making process and how they view their community and surrounding environment. Data on transport, food purchasing, consumption behaviours, and nutrition knowledge as well as an understanding of the relationships between spatial and economic accessibility would therefore enable a better understanding of the associations found within this study.

Additionally, as the spatial exposure data used in this research are from secondary sources it may not adequately characterise the built environment in a way which is intimately connected to the everyday life of individuals or communities. Not only do populations regularly access food and areas for physical activity outside of their direct neighbourhood, but their perception of neighbourhood may differ from the measures used in this study. Therefore, the home and family environment, as well as individual's mobility patterns, are also important areas of research (Chambers et al., 2017; Olsen, Mitchell, McCrorie & Ellaway, 2019). Such research may provide a more detailed understanding of the relationships between built environment variables, consumption and use patterns, and individuals. Overall, the current research is intended to be exploratory in nature, aiding in the detection of broad spatial patterns and associations. Further assessment of the influence of quality, cost, food knowledge, and mobility patterns among other compositional and societal norms through detailed longitudinal studies is needed to fully understand the relationships discussed within this study.

7.5 Chapter summary

In conclusion, this chapter summarises the overarching themes of this thesis, including demographic patterns, economic and spatial accessibility, and the spatial epidemiological nature of T2DM and high childhood weight status. It also provides a discussion of the research limitations as well as the relevant policy intersections. Although the datasets used cannot link the health conditions of T2DM and high weight status in children, and causality cannot be unequivocally demonstrated within the current research, it does provide a basis for understanding spatial patterns of health outcomes relating to both T2DM and high weight status in children. It also offers a deeper understanding of the influence that various aspects of the built environment may have on these health conditions. While these relationships warrant further research, the current study provides valuable insight by identifying spatial patterns and suitable areas for intervention at an environmental level.

Chapter 8 : Research conclusions

The aim of this thesis was to analyse the built environment in urban New Zealand and investigate associations with the spatial epidemiology of two health outcomes: (1) Type 2 Diabetes Mellitus (T2DM), and (2) high weight status in children. This thesis has, in turn, made original contributions to scientific knowledge on associations between health and the built environment. These include the use of both established and novel approaches to measuring various aspects of the built environment as well as analysing data on multiple health issues, for various population groups, for all urban areas of New Zealand using both spatial and statistical methods. Results which analyse built environmental exposures, while mixed, indicate that there is generally increased accessibility to all exposures, both those considered as healthy and those considered as unhealthy, within deprived areas of urban New Zealand. Results also demonstrate that T2DM is more spatially clustered than high weight status in children; however, both are influenced by demographic factors and are associated with accessibility to environmental exposures, notably those considered health-promoting.

This final chapter, research conclusions, focuses on the key findings of this research and the original contributions made by this thesis. It also provides a brief discussion of areas for further research and recommendations. This chapter begins by revisiting and evaluating the research objectives. It then outlines the key points, future areas of research, and recommendations. The thesis then concludes with a final summary.

8.1 Research objectives revisited

There were five main objectives of this research (refer to Chapter 1, section 1.3.1). This section evaluates these objectives in regard to the relevant thesis sections.

The first objective was to review the literature on spatial relationships between the built environment and health, focusing on T2DM and high weight status. This was primarily addressed through Chapter 2, which presented the relevant body of literature. Supporting information on Aotearoa New Zealand which also helps to address this objective was provided in Chapter 3.

The second objective was to create accurate measures of various built environment exposures for comparison with these health outcomes. This was achieved and described in detail throughout Chapter 4 which shows the process of attaining and categorising environmental data as well as the construction of spatial measures. This chapter also provides an analysis and discussion of how these environmental variables relate to socioeconomic status.

The third objective was to investigate the spatial distribution of T2DM and high weight status in children within urban New Zealand. This was achieved through Chapter 5 and Chapter 6 respectively whereby spatial distribution patterns were investigated and exploratory spatial data analysis techniques employed to assess clustering and autocorrelation.

The fourth objective was to examine if there is evidence that T2DM and high weight status in children may be influenced by spatial accessibility to various aspects of the built environment. This objective was again addressed through Chapter 5 and Chapter 6, where the former assessed associations between the built environment and T2DM and the latter associations between the built environment and high weight status in children.

The fifth, and final, objective of this research was to evaluate the overall themes of this thesis and discuss a geospatial understanding of relationships between the built environment and health. This was addressed through the general discussion within Chapter 7, which also discussed the relevant policy initiatives directed toward these health issues.

8.2 Key findings

This study is the first in New Zealand to spatially quantify the effects of environmental exposures on multiple health outcomes of: (1) population level T2DM, and (2) high weight status in children, using geospatial methods and Bayesian modelling, for all urban areas. It is also one of the first to use Data Zones to more accurately reflect the spatial nature of urban areas than boundaries based on administrative units, which are not primarily designed for spatial research.

Overall, it was found that demographic factors are very influential for both T2DM and high weight status in children. Additionally, there was significant spatial variation for both health conditions; however, areas of clustering were far more prominent for T2DM than for high weight status in children. Regarding spatial accessibility of environmental exposures, results demonstrated that both of these health outcomes are more heavily influenced by health promoting resources, notably fruit and vegetable stores and physical activity facilities, than those considered detrimental to health. Exposures considered detrimental to health, such as fast food, takeaways, and dairy/convenience stores demonstrated inconsistent results and indicated little association with health outcomes of either T2DM or high weight status in children, contrary to intuitive appeal. This may indicate that resources considered detrimental to health are not heavily influential for such health outcomes. In contrast, exposures considered health promoting such as fruit and vegetable stores and physical activity facilities had a protective effect on the risk of both health outcomes and showed the most significant results. Interestingly, this relationship was fairly consistent even when considering different health outcomes, T2DM and high weight status, and different population groups, both the whole urban population and children specifically. This is reflective of the current body of literature, which also indicates largely heterogeneous results as discussed previously. Caution must be exercised, however, to ensure that a balanced approach is taken within prevention efforts which addresses the food and physical activity environments as well as economic accessibility, individual behaviours, and societal norms.

8.3 Recommendations and future research

While this research addresses the spatial nature of interactions between the built environment and non-communicable health outcomes of T2DM and high weight status in children it cannot account for all aspects due to the complexities of mediating factors, data limitations, and the study design.

Results should, however, be of interest to policymakers in New Zealand as a better understanding of local environments can not only have significant implications when it comes to addressing inequalities, but also when considering population health outcomes overall. Recommendations which should be considered by policy makers and other relevant bodies include the importance of geospatial research contributions and multisector approaches to invest in the reduction of risk factors and disease prevention, instead of an investment in treatment. This includes policies within sectors such as education, trade, media and marketing, urban planning and development, transport, and health. Such policies should address the contextual influence of physical, economic, and socio-cultural environments which shape individual risk as well as affordability, accessibility, and implementation capacity. This can be achieved by the use of existing frameworks, guidelines, and tools outlined within Chapter 7, Section 7.3 while also accounting for context specific factors and carefully monitoring impact. Further research within at-risk areas, as identified within this thesis, is needed however in order to make significant contributions to policy initiatives.

Future research can also build upon the associations found within this study in various ways. Firstly, re-running models using the most up-to-date data is recommended to ensure results continue to reflect the changing nature of these health outcomes and the built environment. Additionally, studies of longitudinal design are needed in order to understand how such associations may vary over time. Studies which use individual level data to consider the mediating influences of dietary habits and physical activity levels as well as those which consider the interplay between spatial and economic accessibility are also needed. A complex systems approach may also be a valuable area of future research which can investigate how relationships between a systems parts give rise to collective behaviours. Furthermore, future research may benefit from understanding the individual mobility and the home and family environments as well as the neighbourhood environment. While current findings demonstrate limited influence of spatial accessibility as a sole mediator, they do contribute to an improved understanding of the contextual relationship between environmental exposures and health outcomes of T2DM and high weight status in children. Further research on such relationships is warranted to fully understand these associations as well as the societal and cultural norms which lead to their development.

8.4 Concluding statement

The built environment has an important influence on individual, neighbourhood, and population level health outcomes. Evidently, further research is needed to better understand the pathways by which environmental and behavioural relationships may differ depending on region and population group as well as mediating factors. Nevertheless, it is vital to consider such contextual influences in order to understand the spatial epidemiology of non-communicable health outcomes and rising levels of chronic health conditions in Aotearoa New Zealand. Accounting for these contextual influences within both research and policy can not only enhance understandings of such health concerns, but can also identify opportunities for prevention efforts. This thesis has, in turn, provided valuable insight into such associations and a base from which to further address the complexities of such issues using a geospatial approach.

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Appendices

A.1

Appendix A.1

(1) diabetes [MeSH] OR diabetes [tiab] OR type 2 diabetes [MeSH] OR type 2 diabetes [tiab] OR T2DM [MeSH] OR T2DM [tiab] OR obesity [MeSH] OR obesity [tiab] OR childhood obesity [MeSH] OR childhood obesity [tiab] OR body mass index [MeSH] OR body mass index [tiab]

AND

(2) “built environment”[tiab] OR “food environment” [tiab] OR “physical activity environment” [tiab] OR “greenspace” [tiab] OR “recreation facilities” [tiab] OR “environmental determinant(s)” [tiab] OR “local environment” [tiab] OR “environmental characteristic(s)” [tiab] OR “urban environment” [tiab] OR “obesogenic environment” [tiab] OR “neighbourhood characteristic(s)” [tiab] OR “geospatial” [tiab] OR “GIS” [tiab] OR “geographic information systems” [tiab] OR “spatial access” [tiab]

AND

Filters activated: Publication date from 01/01/2000 to 01/06/2018, English language.

Figure A.1: *Literature search terms, example from PubMed*

Appendix A.2

***Table A.1**: Full characteristics of studies included in literature review*

First author	Year	Country	Design[1]	Health condition			HO[2] measure	Domain		Correlates/ sub-domain	OP[3] measure	Association			Geographic measure[4]
				DM[5]	*Weight Status*	*Both*		*Food*	*PA[6]*			*Expected*	*Null*	*Mixed/ Unexpected*	
Adachi-Mejia	2017	USA	CS		x		S	x	x	stores, parks, natural environment, convenience, grocery, fast food, coffee, shopping centre	O + P	x			1km network buffer, 2km proximity measures
Ahern	2011	USA	CS			x	S	x		restaurants, grocery stores	O	x			census tract (county)
AlHasan	2016	USA	CS	x			M	x		fast food, convenience, super store, grocery store	O		x		census tract (county)
Auchincloss	2008	USA	CS	x			M	x	x	healthy foods and activity facilities	O	x			1 mile and closest distance
Auchincloss	2009	USA	LG	x			M	x	x	suitability of the environment for physical activity, availability of healthy foods	P	x			census tract, 1.6km/20 min walk
Barrientos-Gutierrez	2017	USA	LG		x		M	x	x	supermarkets, fruit and vegetable, recreational resources, community perceptions	O + P			x	1 mile buffer
Bell	2008	USA	LG		x		M		x	greenspace	O	x			1km buffer, euclidean and network
Berge	2014	USA	CS		x		M	x		fast food, convenience, supermarket/centre	O		x		1600m, 1200m, 2400m network buffers

Table A.1: *Full characteristics of studies included in literature review … continued*

Black	2010	USA	CS	x	S	x	x	supermarket, restaurant, emergency providers, grocers, fast food, beverage/snack stores, land use, physical activity facilities	O	x			census tract
Black	2009	USA	LG	x	S	x		supermarkets, small grocers, restaurants, snack stores, land use, fitness facilities, crime	O	x			census tract
Block	2011	USA	LG	x	M	x		restaurant (fast food, full-service, bakeries/coffee shops), and food stores (supermarkets, grocery stores, convenience stores)	O		x		driving distance
Bodor	2010	USA	CS	x	S	x		small food stores, medium food stores, supermarkets, convenience stores, fast food	O	x			2km network buffer
Boehmer	2007	USA	CS	x	S		x	recreational facilities, land use, aesthetics	O + P			x	0.4 mile buffer
Boone-Heinonen	2013	USA	LG	x	M	x	x	fast food, supermarket, convenience stores, physical activity facilities, facilities supporting sedentary activities	O			x	3km euclidean buffer
Carroll-Scott	2013	USA	CS	x	M	x	x	retailers and parks (grocery stores, convenience stores, fast food, parks, gym, crime), and perceived	O + P	x			census tract with 20m buffer and shortest network path
Catlin	2003	USA	CS	x	S	x	x	parks, exercise facilities, fruit/veg	P			x	0.5 mile buffer

Table A.1: *Full characteristics of studies included in literature review … continued*

Cerin	2011	USA	CS		x	S	x	x	grocery or convenience stores, specialty stores, fast food, sit-down restaurants	O			x	1km network buffer
Chen	2016a	USA	CS		x	S	x		supermarkets, grocery stores, convenience stores, specialty food stores, full-service restaurants, fast food, bars and taverns	O	x			census tract
Chen	2012	USA	CS		x	S	x	x	fast food, grocery store, sit-down restaurants, park space	O	x			0.5 mile buffer
Chen	2016b	USA	LG		x	M	x		supermarket, fast food, grocery, convenience	O	x			census tract
Chi	2013	USA	CS		x	M	x	x	grocery, convenience, fast food, full-service restaurants, natural amenities	O			x	census tract (county)
Christine	2015	USA	LG	x		M	x	x	supermarket, fruit and vegetable, commercial recreation facilities	O + P	x			1 mile buffer and perceived area
Cunningham	2018	USA	CS	x		M	x	x	park, recreation facility, access to healthy foods, food insecurities	O	x			census tract (county)
Drewnowski	2012	USA	CS		x	S	x		supermarket	O			x	1 mile distance
Drewnowski	2014	USA/ France	CS		x	S	x		supermarket	P		x		distance measure
Duncan	2012	USA	CS		x	S	x	x	walking destinations, community design	O		x		400 and 800m network buffers
Dwicaksono	2018	USA	CS		x	M	x	x	supermarket, fast food, restaurant, farmers market	O	x			census tract
Fan	2014	USA	CS		x	S	x		grocery, convenience, limited/full-service restaurants	O			x	census tract and 1km buffer

Table A.1: *Full characteristics of studies included in literature review … continued*

Frankenfeld	2015	USA	CS			x	S	x		fast food, convenience, grocery, specialty food	O			x	census tract
Gebreab	2017	USA	LG	x			M	x	x	favourable and unfavourable stores, activity resources	O + P	x			1 mile buffer
Ghimire	2017	USA	CS		x		S		x	greenspace	O	x			census tract (county)
Gibson	2011	USA	LG		x		S	x		supermarkets, small grocery stores, convenience and specialty food stores, limited service, full service restaurants	O	x			census tract
Gordon-Larsen	2006	USA	CS		x		M		x	physical activity facilities	O	x			8.05km buffer
Grafova	2008	USA	CS		x		M	x		restaurant, grocery and convenience store	O	x			census tract
Hattori	2013	USA	CS		x		S	x		fast food, restaurants, convenience, small food stores, grocery stores, supermarkets	O		x		0.25, 0.5, 1.0, 1.5 and 3 mile euclidean buffers
Haynes-Maslow	2017	USA	CS	x			S	x		grocery, supercentres, markets, restaurants, fast food, convenience	O			x	census tract (county)
Herrick	2016	USA	CS	x			M	x		supermarket, walkability	O	x			census tract
Hosler	2016	USA	CS		x		S	x		supermarket, ethnic market, food co-op, farmers markets, produce, convenience	O			x	census tract and 1 mile network buffer
Hughey	2017	USA	CS		x		M		x	parks and playgrounds	O			x	census tract
Hutchinson	2012	USA	CS		x		S	x		healthy and unhealthy foods	O			x	census tract
Inagami	2009	USA	CS		x		S	x		fast food, restaurants	O	x			census tract
Jeffery	2006	USA	CS		x		S	x		fast food	O		x		0.5, 1, 2 mile buffers

Table A.1: *Full characteristics of studies included in literature review … continued*

Jilcott	2011a	USA	CS	x		S	x		farmers markets, grocery, supermarkets, supercentres	O	x			census tract (county)
Jilcott	2011b	USA	CS	x		M	x		fast food, restaurants, convenience, produce, supermarket, grocery,	O			x	0.25, 0.5, 1, 5 mile network buffers
Koleilat	2012	USA	CS	x		M	x		fast food, convenience stores, supermarkets and other grocery stores, produce	O			x	census tract
Kruger	2014	USA	CS	x		S	x		fast food	O	x			2 mile buffer
Laska	2010	USA	CS	x		M	x		fast food, convenience stores, grocery stores	O + P			x	800m, 1600m, 3000m network buffers
Lee	2017	USA	LG		x	M	x	x	intersection density, greenspace, recreation land, food stores	O			x	census tract
Li	2009a	USA	CS	x		M	x	x	fast food, walkability	O	x			census tract
Li	2009b	USA	CS	x		M	x		fast food	O	x			census tract
Li	2016	USA	CS	x		S	x		supermarket, convenience, fruit and vegetable, full and limited service restaurants	O	x			census tract (county)
Liu	2007	USA	CS	x		M	x	x	vegetation, supermarket, grocery stores, fast food, convenience stores	O	x			2km buffer and proximity
Lopez	2007	USA	CS	x		S	x		retail density, establishment density, supermarket, fast food	O			x	census tract
Maddock	2004	USA	CS	x		S	x		fast food	O	x			census tract
Mejia	2015	USA	CS	x		S	x		fast food, convenience, small food stores, grocery stores, supermarkets	O		x		census tract and 0.25, 0.5, 1.0, 1.5, 3.0 mile euclidean buffers

Table A.1: *Full characteristics of studies included in literature review … continued*

Meyer	2015	USA	LG		x	M	x	x	convenience, food stores, supermarkets, grocery, fast food, restaurants, activity facilities, parks	O		x		3km network and euclidean buffer
Michimi	2015	USA	CS	x		S	x		supermarket, convenience stores, full service restaurants, fast food, snack/coffee	O	x			census tract
Morland	2009	USA	CS	x		S	x		supermarket, grocery, convenience store, specialty food store, full service restaurant, fast food, limited service restaurant	O	x			census tract
Morland	2006	USA	CS		x	S	x		supermarket, convenience stores, full-service restaurants, fast food	O			x	census tract
Mujahid	2008	USA	CS	x		M	x	x	aesthetic quality, walking environment, availability of health foods	P	x			census tract and 1 mile buffer
Myers	2016	USA	CS	x		M	x	x	fitness and recreation facilities, grocery stores, fast food	O	x			census tract (county)
Nesbit	2014	USA	CS	x		S		x	sidewalks, parks and playgrounds, community centres	O + P	x			census tract
Newman	2014	USA	CS	x		M	x		fast food	O	x			census tract (county)
Norman	2006	USA	CS	x		M		x	recreational facilities, parks, community design	O		x		1 mile buffer
Ohri-Vachaspati	2013	USA	CS	x		M	x	x	food and physical activity outlets	O			x	census tract, 1/4, 1/2 and 1 mile buffers
Oka	2013	USA	CS	x		M	x	x	convenience, grocer, gym, greenspace	O		x		census tract

Table A.1: *Full characteristics of studies included in literature review … continued*

Oreskovic	2009	USA	CS		x		M	x	x	fast food, open space	O		x		census tract, 400m buffer and distance
Piccolo	2015	USA	CS	x			M + S	x	x	open space, grocery stores, convenience stores, fast food	O		x		census tract
Rose	2009	USA	CS		x		S	x		supermarkets, grocery	O			x	census tract
Rummo	2017	USA	LG		x		S	x		fast food, restaurants, convenience stores, supermarkets	O			x	1km network buffer
Rundle	2009	USA	CS		x		M	x		big-healthy, big-intermediate, big-unhealthy	O			x	0.5 mile euclidean buffer
Saelens	2012	USA	CS		x		M	x	x	favourable and unfavourable	O	x			census tract
Salois	2012	USA	CS			x	S	x		supermarkets, grocery stores, supercentre, convenience stores, farms with direct sales, farmers markets, fast food, full-service restaurants	O	x			census tract
Sander	2017	USA	CS		x		M		x	greenspace	O			x	census tract
Schwartz	2011	USA	CS		x		M		x	activity facilities, park projects and preserved areas	O			x	0.5 mile network buffer and census tract
Shier	2012	USA	LG		x		M	x		food environment indices, outlet combinations	O			x	census tract
Slack	2014	USA	CS		x		S	x	x	recreational context, food environment,	O			x	census tract (county)
Slater	2010	USA	CS		x		S		x	safety, outdoor and commercial physical activity settings	O	x			community based on census block level

Table A.1: *Full characteristics of studies included in literature review … continued*

Stark	2013	USA	CS		x	S	x		supermarkets, fruit and vegetable, natural food, fast food, pizza, convenience, grocery	O	x			census tract
Stewart	2011	USA	CS	x		M	x		fast food, convenience	O		x		census tract
Sullivan	2014	USA	CS		x	S	x	x	clubs, playground/park/open space, supermarket, library, leisure time	P	x			census tract
Thomsen	2016	USA	LG		x	M	x		food desert	O	x			census tract
Tilt	2006	USA	CS		x	S		x	greenery	O + P			x	0.4mile network buffer and self-report
Truong	2010	USA	CS		x	S	x		physical food environment index	O	x			census tract
Turi	2017	USA	CS	x		M	x		food environment	O	x			census tract
Wang	2007	USA	CS		x	S	x		fast food and food retail	O			x	census tract
West	2012	USA	CS		x	S		x	park land (area)	O	x			metropolitan statistical area
Wolch	2011	USA	LG		x	M		x	urban parks and recreational resources	O	x			500m and 10km buffers
Xu	2015a	USA	CS		x	S	x	x	fast food, full service restaurant, walkability	O			x	census tract (county)
Xu	2015b	USA	CS		x	S	x	x	fast food, full service restaurant, street connectivity, walkability	O			x	census tract (county)
Yan	2015	USA	CS		x	S	x		supercentres, convenience, grocery, specialty food stores	O	x			census tract (county)
Zhang	2017	USA	CS	x		M	x		supermarket access	O		x		census tract
Zick	2009	USA	CS		x	S	x	x	walkability, healthy grocery, convenience, restaurants, fast food	O			x	census tract

Table A.1: *Full characteristics of studies included in literature review … continued*

Ghenadenik	2018	Canada	LG		x	M	x	x	physical activity facilities, convenience stores, fast food	O			x	200m - 400m network buffer
Hollands	2014	Canada	CS		x	S	x		fast food and full service restaurants	O	x			census tract
Kestens	2012	Canada	CS		x	S	x		corner stores, restaurants, fruit and vegetable stores, supermarkets	O			x	census tract
Larsen	2015	Canada	CS		x	M	x		fast food, less healthy/healthy food outlets, supermarket	O	x			1km walk and distance to closest
Le	2016	Canada	CS		x	M	x		restaurants, grocery stores, convenience stores, specialty food stores	O		x		500m and 800m network buffers
Ngom	2016	Canada	CS	x		M		x	greenspace, sports facilities	O	x			census tract
Polsky	2016	Canada	CS		x	S	x		fast food, full service, and other restaurants	O	x			census tract and 720m buffer
Potestio	2009	Canada	CS		x	M		x	parks, greenspace	O		x		census tract
Pouliou	2010	Canada	CS		x	S	x	x	fast food, convenience, grocery, recreational activity facilities	O	x			1km network buffer
Prince	2011	Canada	CS		x	S	x	x	recreation environment, grocery, convenience, specialty food store, fast food and limited service restaurants	O			x	neighbourhoods based on natural boundaries
Prince	2012	Canada	CS		x	S	x	x	as above	O			x	natural boundaries
Spence	2009	Canada	CS		x	S	x		retail food environment index	O			x	800m and 1600m buffer
Veugelers	2008	Canada	CS		x	M	x	x	produce retailers, access to parks and playgrounds, access to recreational facilities	P	x			census tract

Table A.1: *Full characteristics of studies included in literature review … continued*

Corrêa	2018	Brazil	CS		x		M	x		fast food, restaurants, snack bars, supermarkets, mini markets, butchers and greengrocers/public markets	O + P			x	400m euclidean buffer
Cunningham-Myrie	2015	Jamaica	CS			x	M		x	recreation facilities	P		x		census tract
Jaime	2011	Brazil	CS		x		S	x	x	fast food, fruit and vegetable, park density and public sport facilities	O			x	census tract
Mendes	2013	Brazil	CS		x		S	x	x	supermarket, hypermarket, parks, physical activity facilities	O		x		census tract
Velásquez-Meléndez	2013	Brazil	CS		x		S	x	x	parks, locations for exercise, supermarket, fruit and vegetable	O + P			x	census tract
Astell-Burt	2015	Australia	CS	x			S	x		green grocers, supermarkets, takeaways, alcohol outlets	O	x			1.6km network buffer
Carroll	2016	Australia	LG	x			M		x	open space, walkability	O			x	1600m network buffer
Carroll	2017	Australia	LG	x			M	x		fast food, healthful food	O		x		1600m network buffer
Christian	2011	Australia	CS		x		S	x	x	walkability, healthy/ unhealthy outlets, activity destinations, greenspace	O + P		x		1.6km network buffer objective, 10-15min walk perceived
Feng	2018	Australia	LG		x		S	x		fast food, green grocers and supermarkets	O			x	0.4km, 0.8km, 1.6km, 3.2km network buffers
Giles-Corti	2003	Australia	CS		x		S		x	recreational facilities, transport, street typology	O + P	x			census tract

Table A.1: *Full characteristics of studies included in literature review … continued*

King	2016	Australia	CS	x		S	x	x	educational facilities, café, takeaway stores, transport stops and stations, supermarkets, sports facilities, community resources, small food stores	O	x			400m, 800m and 1200m kernel density estimate
Miller	2014	Australia	CS	x		S	x		fast food, healthy food	O	x			800m and 3000m network buffers and distance
Murphy	2017	Australia	CS	x		S	x		supermarket, fast food	O			x	census tract, 800m, 1000m, 1600m, 2000m, 3000m network buffer, distance
Paquet	2014	Australia	LG		x	M	x	x	unhealthful/healthful food resources, walkability	O	x			1000m network distance
Pereira	2013	Australia	CS	x		S		x	greenness	O	x			1600m network buffer
Timperio	2010	Australia	LG + CS	x		M + S		x	public open spaces, sports options,	O			x	800m and 2km buffer
Jenkin	2015	New Zealand	CS	x		M	x	x	green space, food shops, sports/leisure facilities	O			x	census tract
Pearce	2009	New Zealand	CS	x		M	x		fast food outlet	O		x		census tract
Pearson	2014	New Zealand	CS	x		M	x	x	food outlets, greenspace, physical activity facilities	O			x	census tract
Richardson	2013	New Zealand	CS	x		M	x		greenspace	O		x		census tract
Patel	2017	India	CS	x		M	x		full service and fast food restaurants	O	x			census tract, 1km buffer
Xu	2013	China	LG	x		M	x		fast food	O	x			census tract, 1km buffer

Table A.1: *Full characteristics of studies included in literature review … continued*

Zhang	2016	China	LG		x	M	x		grocery store, free market, restaurant	O			x	euclidean proximity
Choo	2017	South Korea	CS		x	M	x	x	Korean fast food, western fast food, activity outlets, nature facilities	O + P		x		200m buffer and distance to nearest
Hanibuchi	2011	Japan	CS		x	S	x		supermarkets, convenience stores, fast food outlets	O			x	500m network buffer, distance to nearest
Mowafi	2012	Egypt	CS		x	M		x	greenspace, recreational facilities	O		x		neighbourhood (defined as 0.7km squared)
Bodicoat	2014	UK	CS	x		M		x	greenspace	O	x			3km euclidean buffer
Bodicoat	2015	UK	CS	x		M	x		fast food	O	x			500m buffer
Burgoine	2011	UK	CS		x	M	x	x	takeaway, restaurant, supermarkets, green grocers, convenience	O			x	census tract
Burgoine	2017	UK	CS		x	M	x		supermarket	O	x			census tract
Cetateanu	2014	UK	CS		x	M	x		fast food outlets, other unhealthy outlets, mixed food outlets	O			x	census tract
Coombes	2010	UK	CS		x	S		x	greenspace	O		x		census tract and distance to the nearest
Cummins	2012	UK	CS		x	S		x	greenspace	O			x	census tract
Dalton	2016	UK	LG	x		M + S		x	greenspace	O	x			800m euclidean buffer
Edwards	2010	UK	CS		x	M	x	x	supermarket, leisure facilities, transport	O			x	census tract
Fraser	2010	UK	CS		x	M	x		fast food	O	x			census tract and distance to the nearest
Gilliland	2012	UK	CS		x	S	x	x	recreation opportunities, fast food outlets, convenience store	O	x			500m and 1000m euclidean and network buffers

Table A.1: *Full characteristics of studies included in literature review … continued*

Griffiths	2014	UK	CS	x	M	x		supermarket, takeaway, retail	O		x		2km euclidean buffer, distance
Harrison	2011	UK	CS	x	M	x	x	healthy outlets, unhealthy outlets, open land area, land use mix	O			x	800m network buffer
Hobbs	2018	UK	CS	x	S		x	unfavourable and favourable activity environments based on parks and physical activity facilities	O			x	2km euclidean buffer
Hobbs	2017	UK	CS	x	S	x		supermarkets, takeaways, other retail outlets	O			x	census tract, 800m and 2000m buffers
Hobbs	2017	UK	CS	x	S		x	parks	O		x		census tract
Howard Wilsher	2016	UK	CS	x	M	x		unhealthy foods	O	x			census tract
Jennings	2011	UK	CS	x	M	x		BMI-healthy outlets, BMI-unhealthy outlets, BMI-intermediate	O	x			800m network buffer
Macdonald	2011	UK	CS	x	S	x		supermarket, general store, fruit/vegetable	O			x	500m, 1000m network
Pearce	2018	UK	LG	x	M	x		fast food	O	x			census tract and 1km network buffer
Sarkar	2017	UK	CS	x	M		x	greenness	O	x			500m catchment area
Schalkwijk	2018	UK	LG	x	M		x	greenspace, garden accessibility	O	x			census tract
Ellaway	2016	Scotland	CS	x	M		x	activity facilities	O	x			census, time
Gose	2013	Germany	LG	x	M	x	x	perception of environment, food outlets, playground and/or greenspace	O + P		x		800m euclidean buffer
Lakes	2016	Germany	CS	x	M	x	x	parks and playgrounds, fast food	O		x		census tract
Lange	2011	Germany	CS	x	M	x	x	energy-dense food supply, fields, parks	O	x			census tract

Table A.1: *Full characteristics of studies included in literature review … continued*

Hamano	2017	Sweden	LG		x	M	x		fast food	O	x		census tract and 1000m buffer
Mezuk	2016	Sweden	LG	x		M	x		fast food, convenience, sit-down restaurant, grocery store	O	x		census tract and 1000m buffer
Casey	2012	France	CS		x	M	x	x	physical activity facilities, groceries, fruit/vegetable, supermarket, fast food	O		x	1000m radius and euclidean distance
Putrik	2015	Netherland	CS		x	S	x	x	shopping facilities, parking facilities, greenspace	P		x	census tract (buurt code)
Nielsen	2007	Denmark	CS		x	S		x	garden/greenspace	P	x		distance measure
Santana	2009	Portugal	CS		x	S	x	x	groceries, supermarkets, green parks, sports facilities	O		x	neighbourhood (aggregate area but undefined)
Raftopoulou	2017	Spain	CS		x	S		x	greenspace	O	x		census tract
Ellaway	2005	Europe	CS		x	S		x	greenery	O	x		residential area

[1]CS = cross-sectional, LG = longitudinal
[2]HO: Health Outcome measure. S = self-reported, M = measured
[3]OP: Objective or Perceived environmental exposure measure. O = objective, P = perceived
[4]Geographic Measures: ‘m’ = metres, ‘km’ = kilometres
[5]DM: Diabetes Mellitus, referring to Type 2 (T2DM)
[6]PA: Physical Activity

Appendix B.1

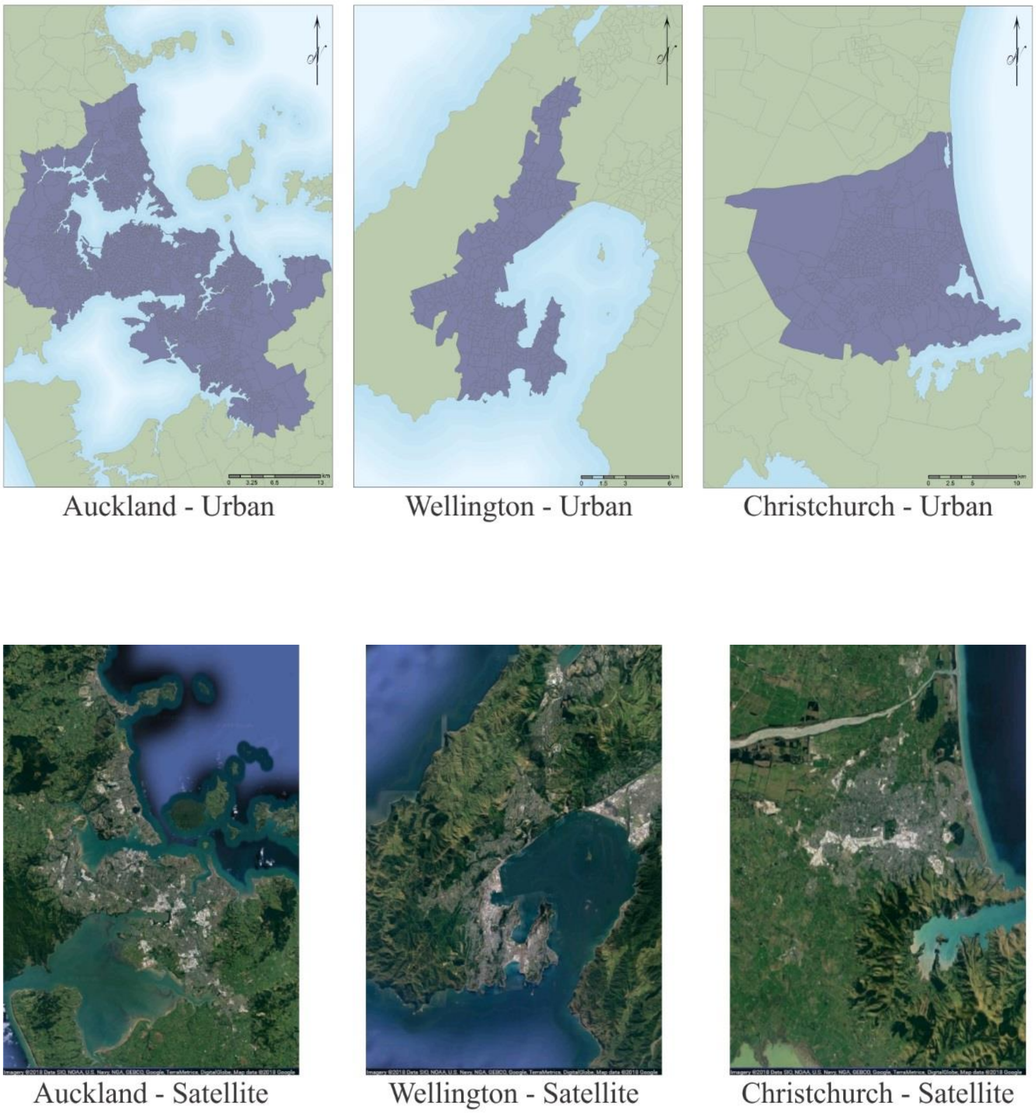

Figure B.1: *Three major urban areas of Auckland, Wellington, and Christchurch (vector and satellite)*

Appendix B.2

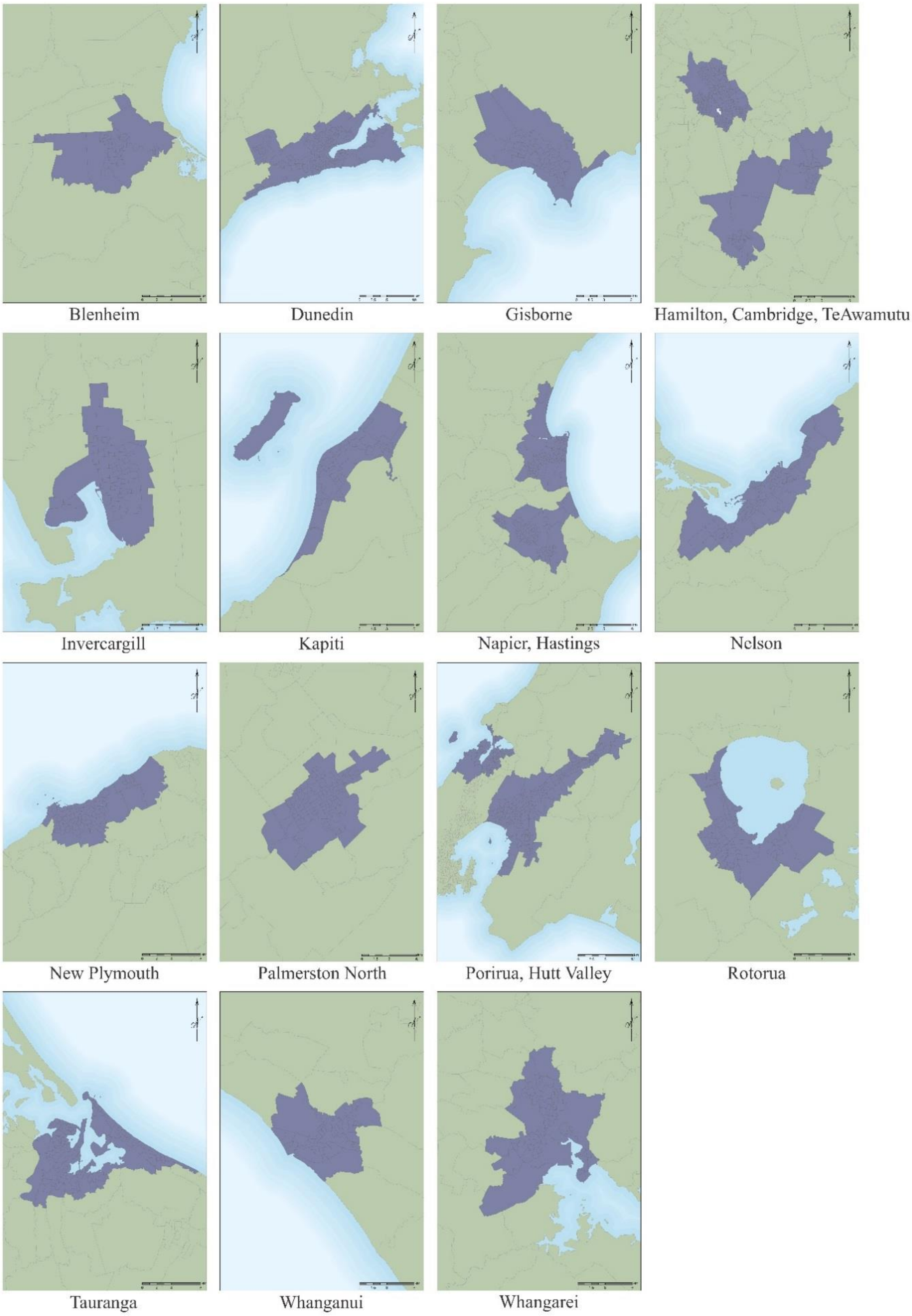

***Figure B.2**: All other main urban areas of New Zealand (vector)*

Appendix C.1

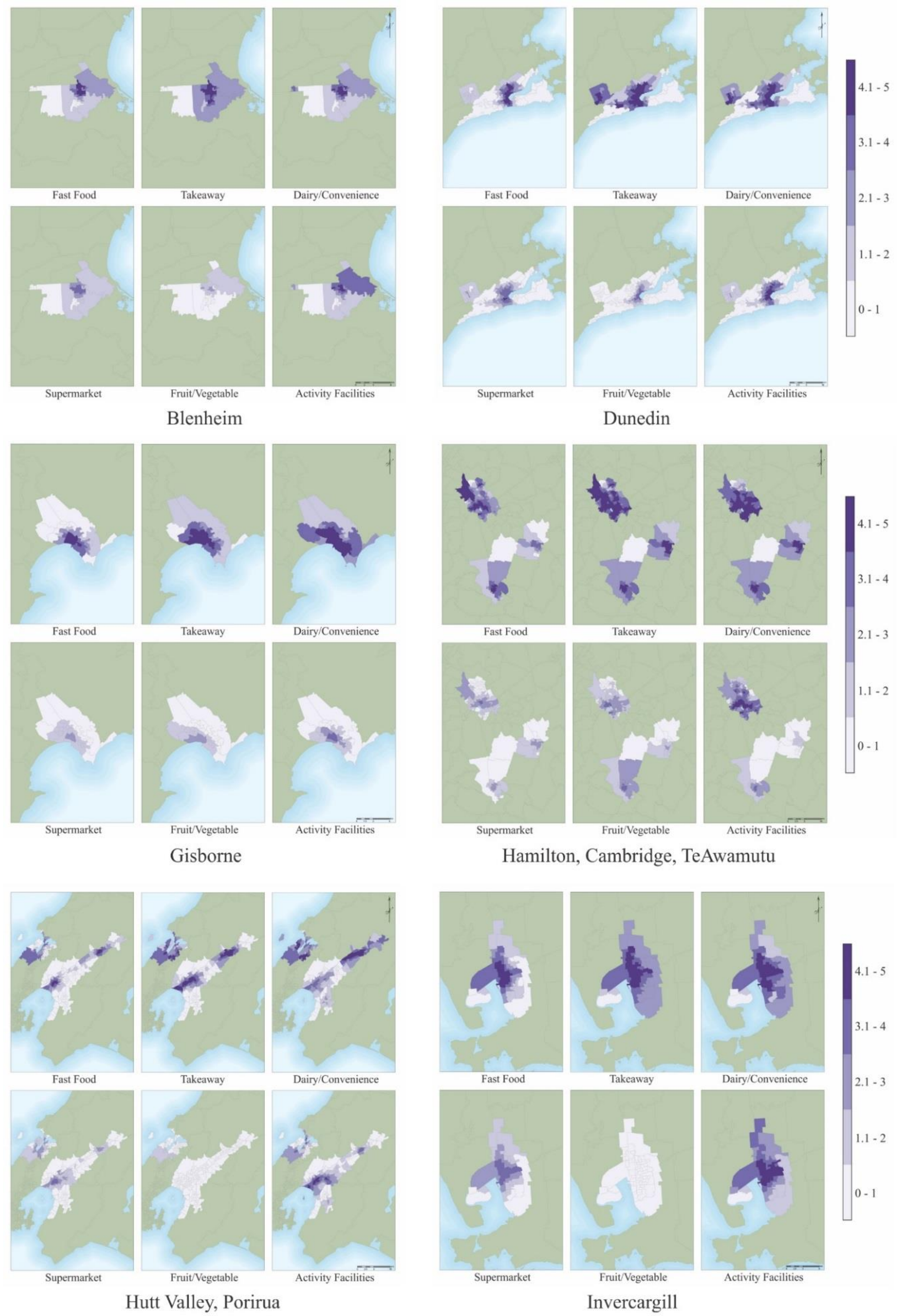

Figure C.1: *Additional E2SFCA results for 'other' urban areas*

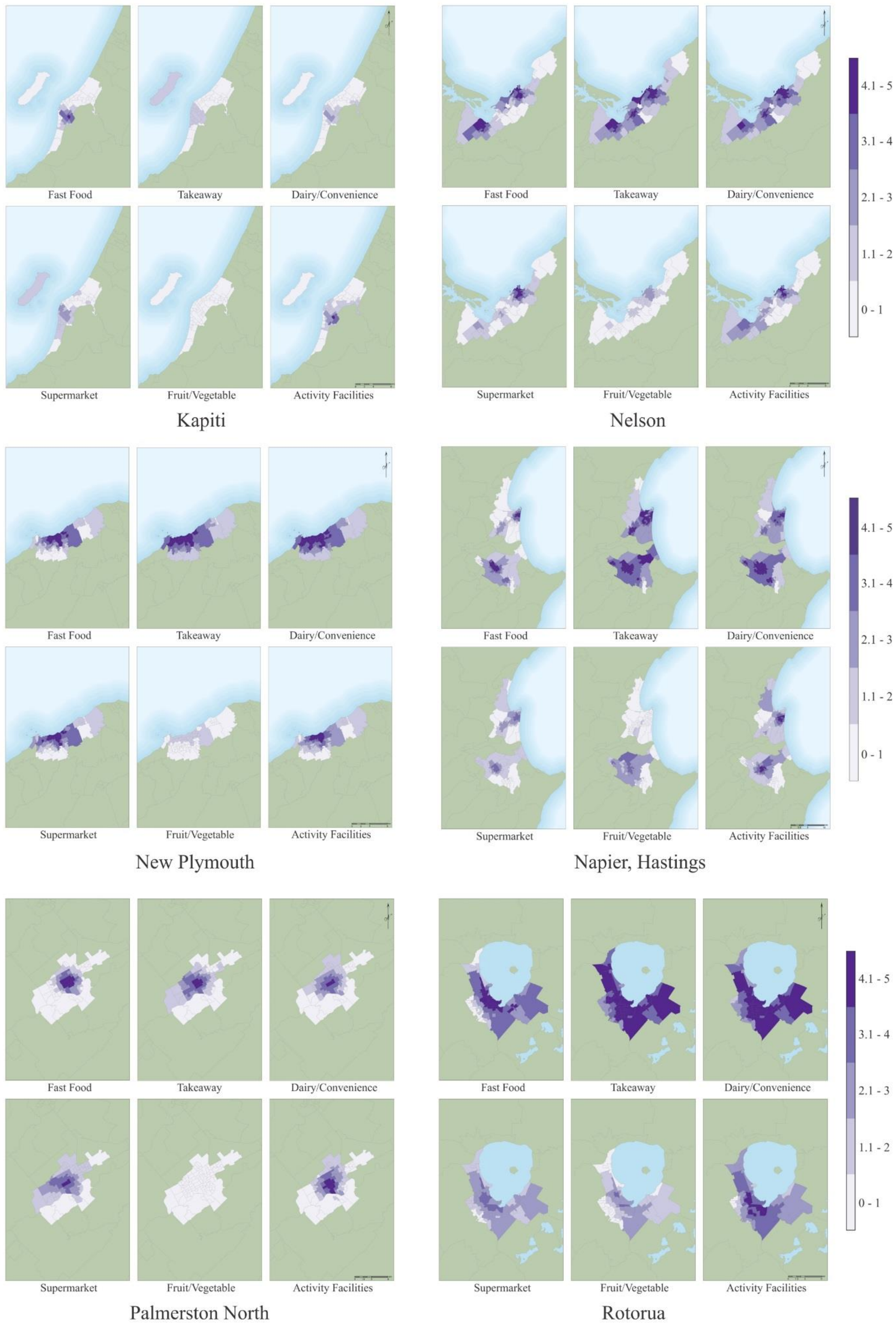

Figure C.1 … (continued): *Additional E2SFCA results for 'other' urban areas*

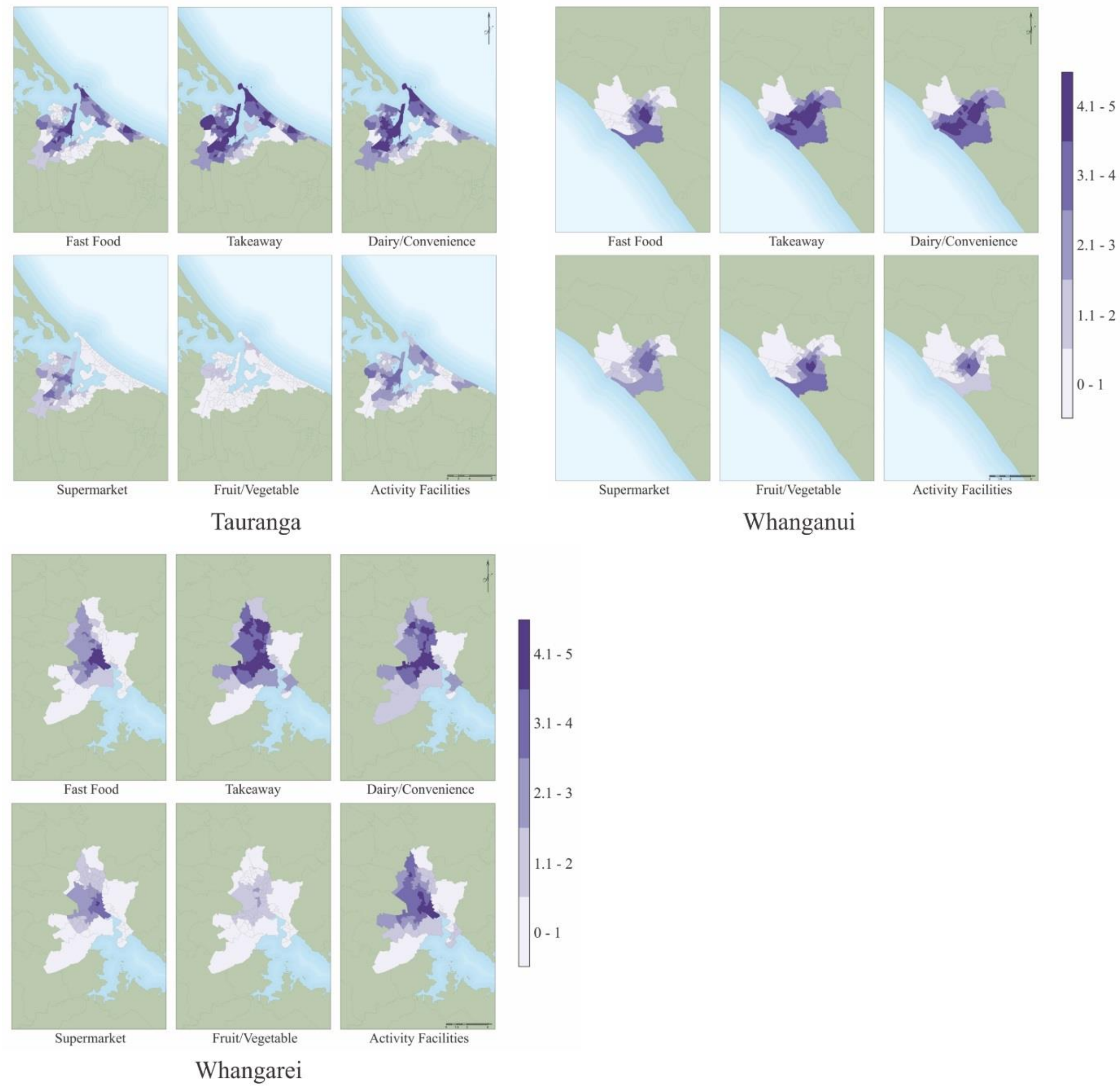

Figure C.1 … (continued): *Additional E2SFCA results for ‘other’ urban areas*

Appendix D.1

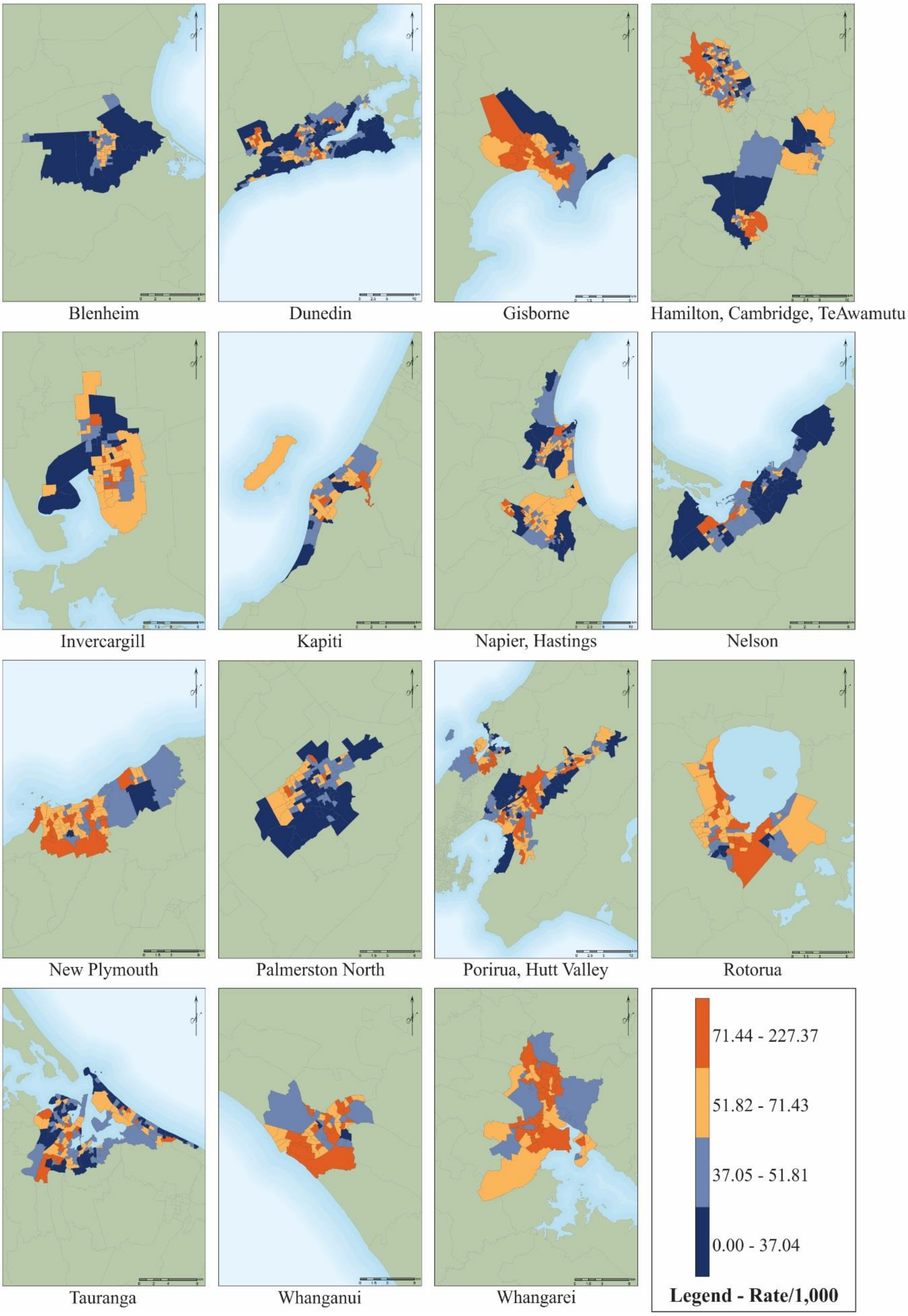

Figure D.1: *Other urban areas – Crude rate per 1,000 (T2DM)*

Appendix D.2

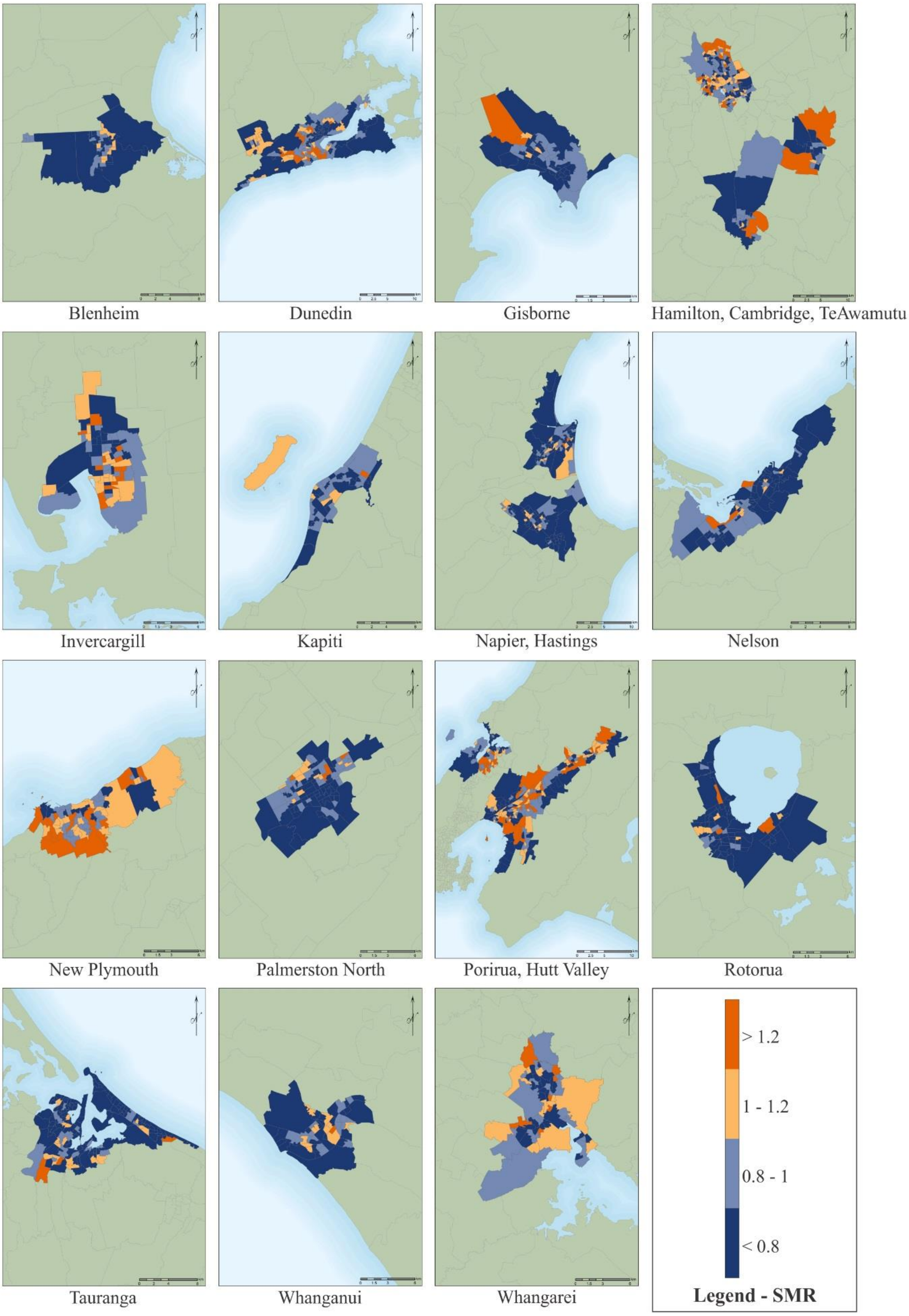

Figure D.2: *Other urban areas – SMR (T2DM)*

Appendix D.3

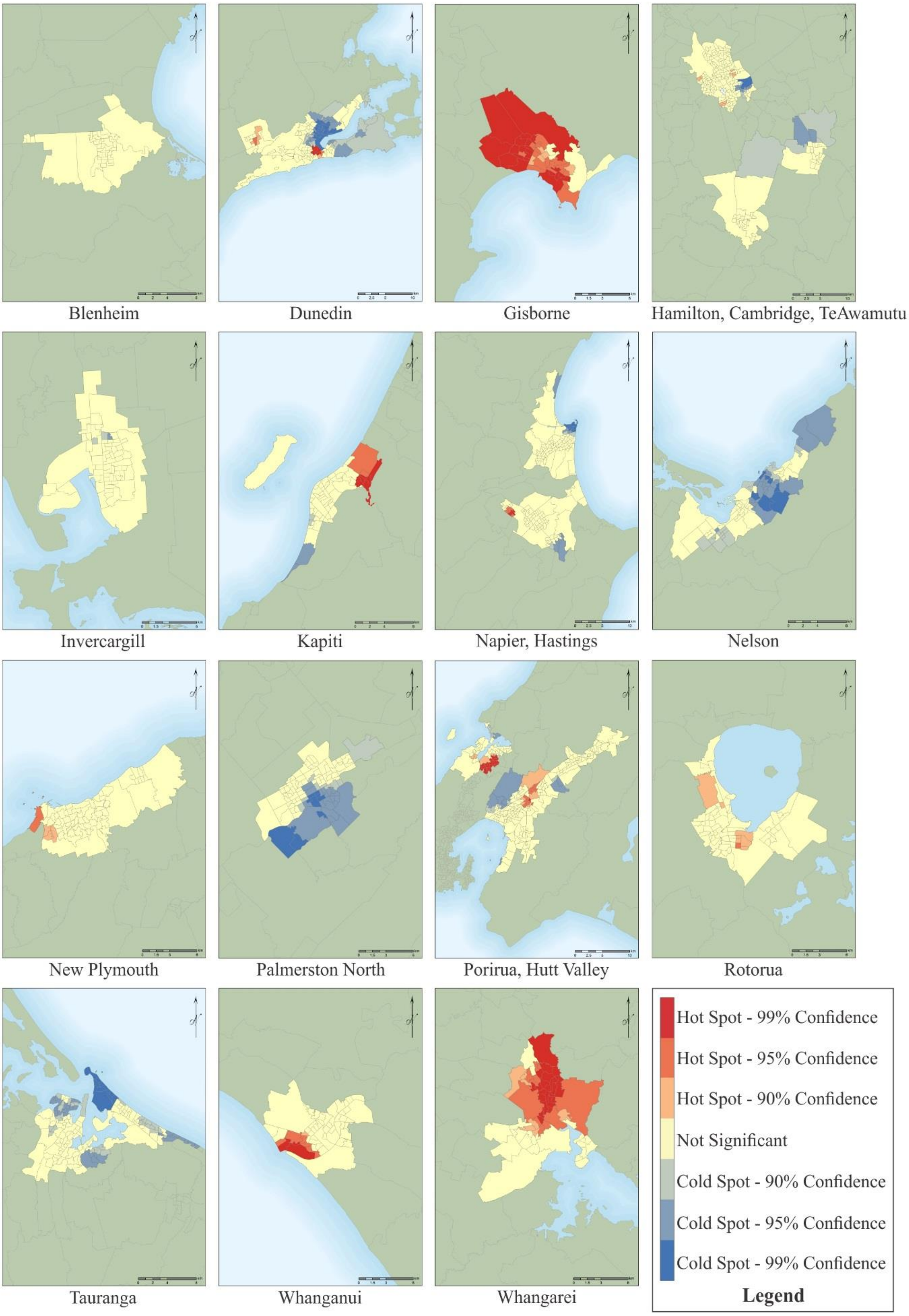

Figure D.3: *Other urban areas – Clustering (T2DM Crude rate per 1,000)*

Appendix D.4

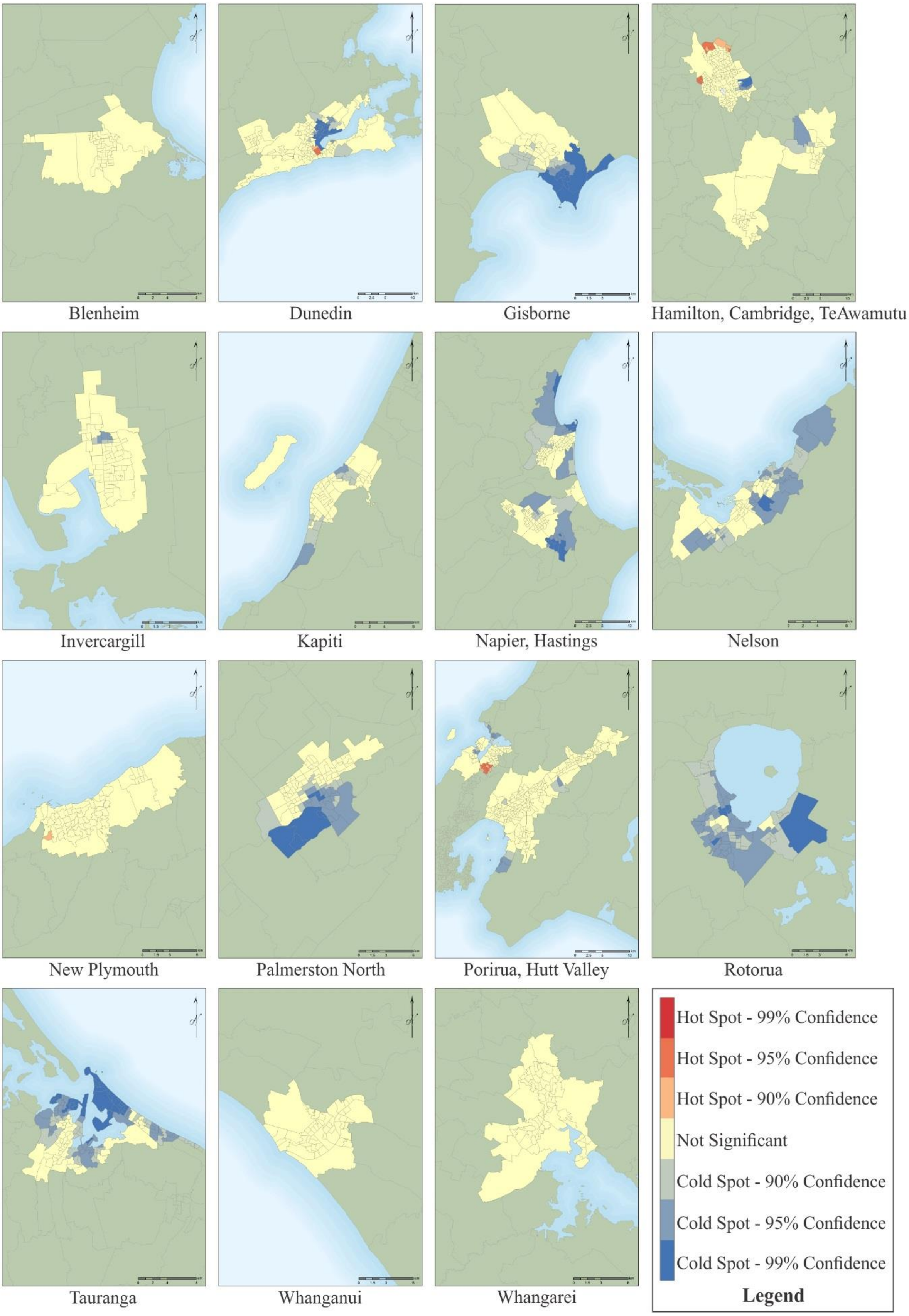

Figure D.4: *Other urban areas – Clustering (T2DM SMR)*

Appendix D.5

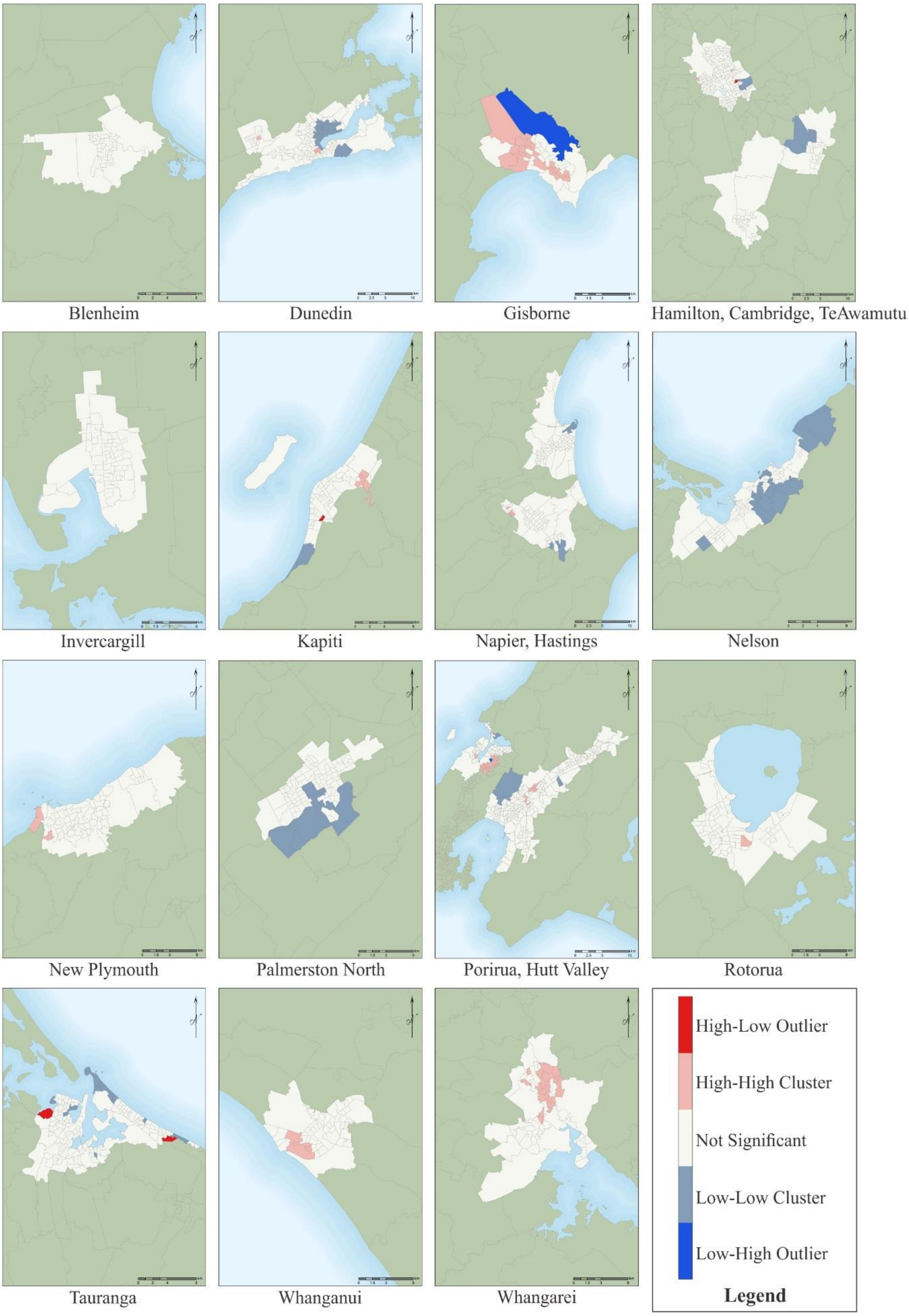

Figure D.5: *Other urban areas – Autocorrelation (T2DM Crude rate per 1,000)*

Appendix D.6

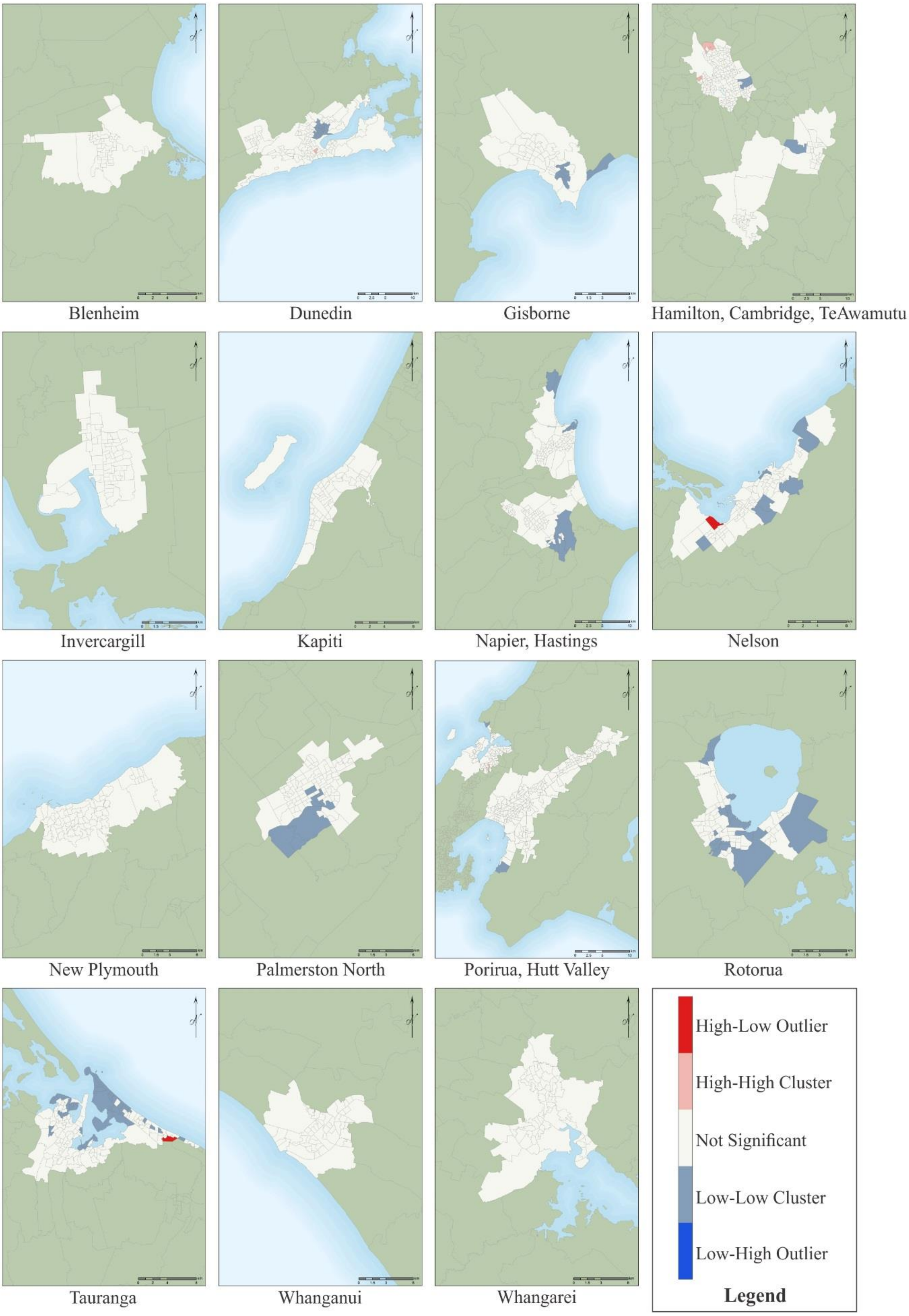

Figure D.6: *Other urban areas – Autocorrelation (T2DM SMR)*

Appendix D.7

Table D.1: *Variance Inflation Factor results for multicollinearity from non-spatial models*

	Model						
	1 E2SFCA	2 E800	3 E1600	4 E3000	5 N800	6 N1600	7 N3000
Fast Food	2.69	1.97	2.78	6.38	1.84	2.38	5.22
Takeaway	3.57	2.57	3.17	8.18	2.33	3.40	6.18
Dairy/Convenience	3.71	2.16	3.26	4.22	1.91	2.88	3.76
Supermarket	1.81	1.23	1.43	1.85	1.24	1.34	1.73
Fruit/Vegetable	1.65	1.16	1.37	1.71	1.14	1.33	1.55
Activity Facilities	2.28	1.45	1.87	2.61	1.39	1.66	2.22
IMD*	1.06	1.06	1.08	1.07	1.06	1.07	1.07
Greenspace – Private	-	1.21	1.38	1.51	1.08	1.23	1.62
Greenspace – Public	-	1.10	1.13	1.11	1.03	1.11	1.30

*IMD no access, continuous measure (all 2 d.p.)
E2SFCA: Enhanced Two-Step Floating Catchment Area
E: Euclidean-based buffer measures (in metres)
N: Network-based buffer measures (in metres)

Appendix D.8

Table D.2: *Diagnostic criteria for model fit*

Model	AIC*	DIC**
1 - E2SFCA	45855	29265
2 - E800	46775	29332
3 - E1600	45951	29394
4 - E3000	46319	29277
5 - N800	47532	29278
6 - N1600	46528	29332
7 - N3000	46385	29326

* Akaike Information Criterion from non-spatial regression models
** Deviance Information Criterion from spatial regression models
E2SFCA: Enhanced Two-Step Floating Catchment Area
E: Euclidean-based buffer measures (in metres)
N: Network-based buffer measures (in metres)

Appendix D.9

Table D.3: *Geweke diagnostics from spatial regression models*

	Model						
	1 E2SFCA	2 E800	3 E1600	4 E3000	5 N800	6 N1600	7 N3000
Intercept	-1.7	1.2	0.9	0.8	0.1	0.2	1.7
Fast Food	-0.8	1.4	1.7	-1	0.2	0.4	0.6
Takeaway	-1.5	-1	-1.3	-0.4	-0.3	0.1	-0.9
Dairy/Convenience	1.6	-0.8	1.1	-0.3	-0.1	0.2	-1.8
Supermarket	0.4	-0.6	-1.6	0	-0.4	-0.1	1.6
Fruit/Vegetable	-0.2	0.2	-1.6	0.2	-1.7	-1.1	-1.8
Activity Facilities	0	-1.3	0.6	0.6	1.1	-0.7	1.6
Greenspace – Private	-	-1.8	0.4	-0.3	0.3	0.9	-0.7
Greenspace – Public	-	-1.2	-1.8	-0.5	1.8	0.1	-0.8

All values given at 2 d.p.
E2SFCA: Enhanced Two-Step Floating Catchment Area
E: Euclidean-based buffer measures (in metres)
N: Network-based buffer measures (in metres)

Appendix E.1

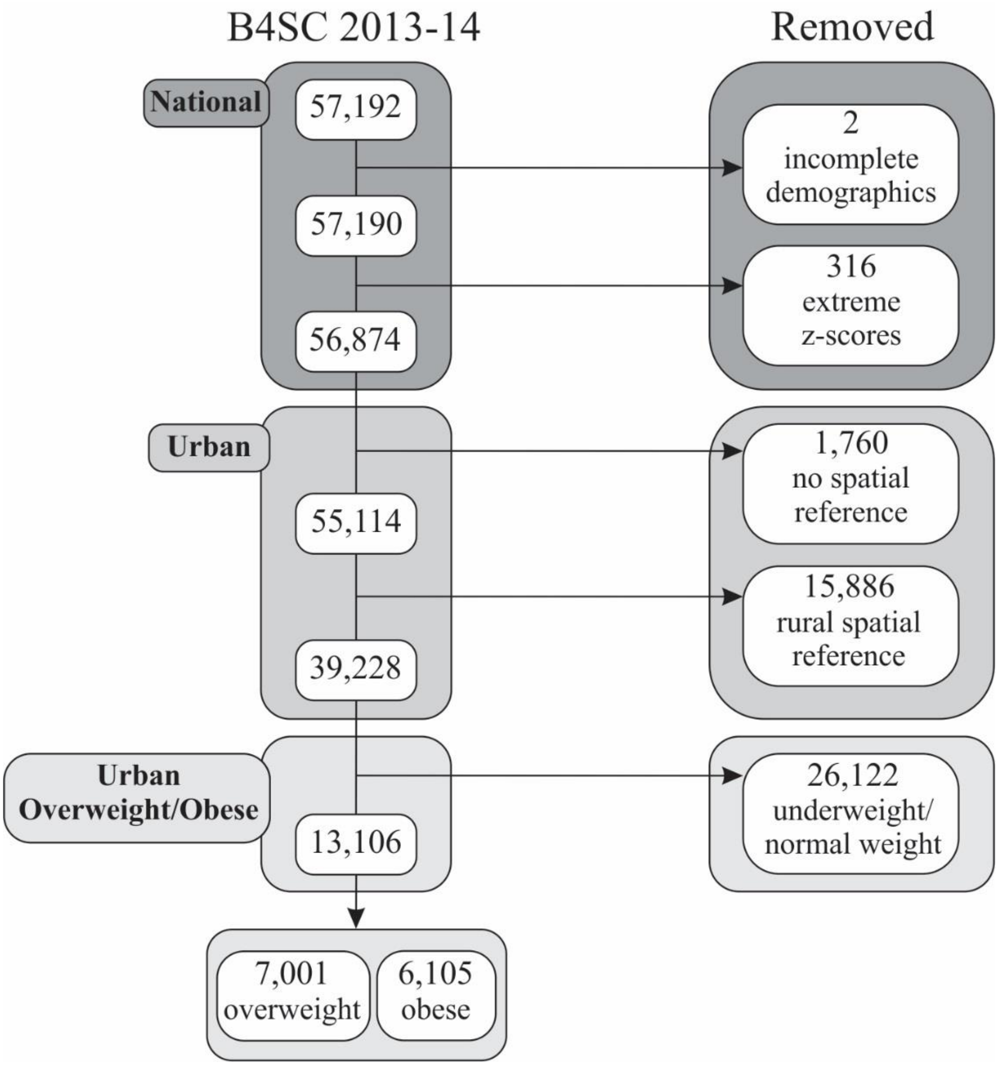

Figure E.1: *B4SC data eligibility, annual details 2013-14*

Appendix E.2

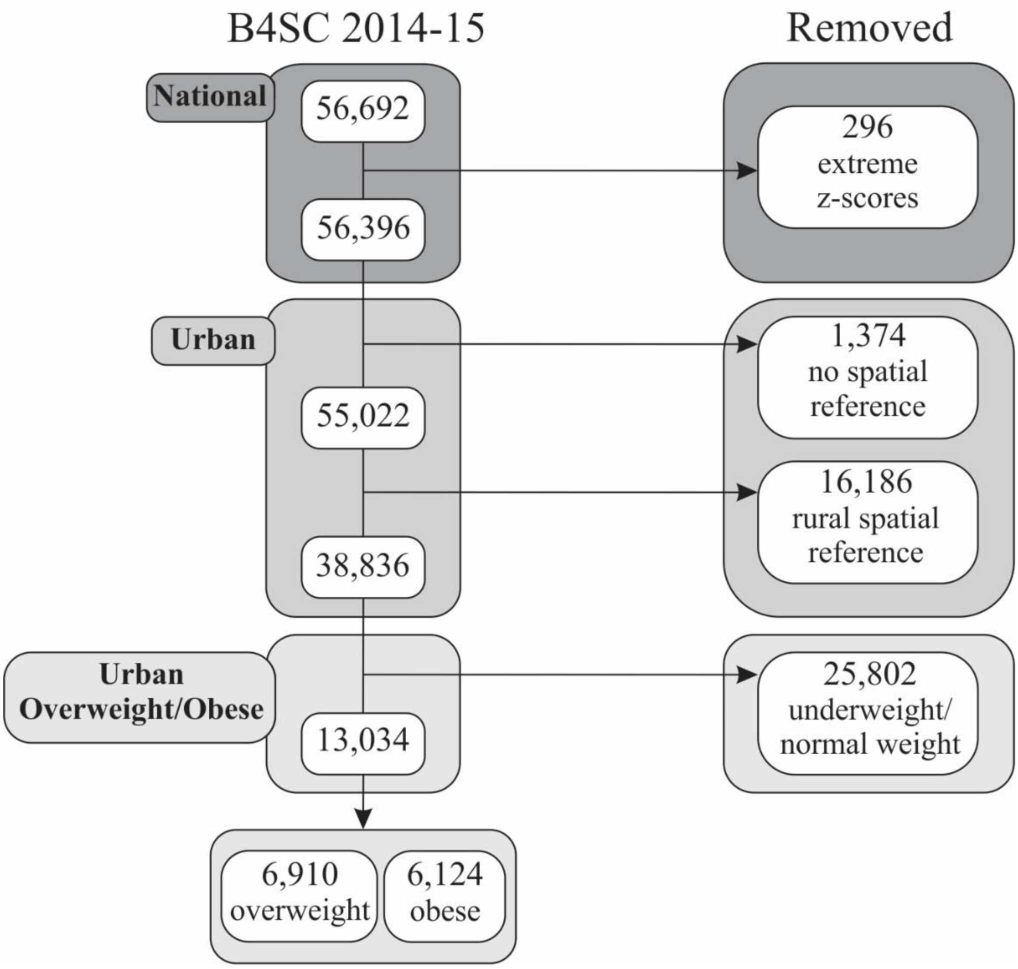

Figure E.2: *B4SC data eligibility, annual details 2014-15*

Appendix E.3

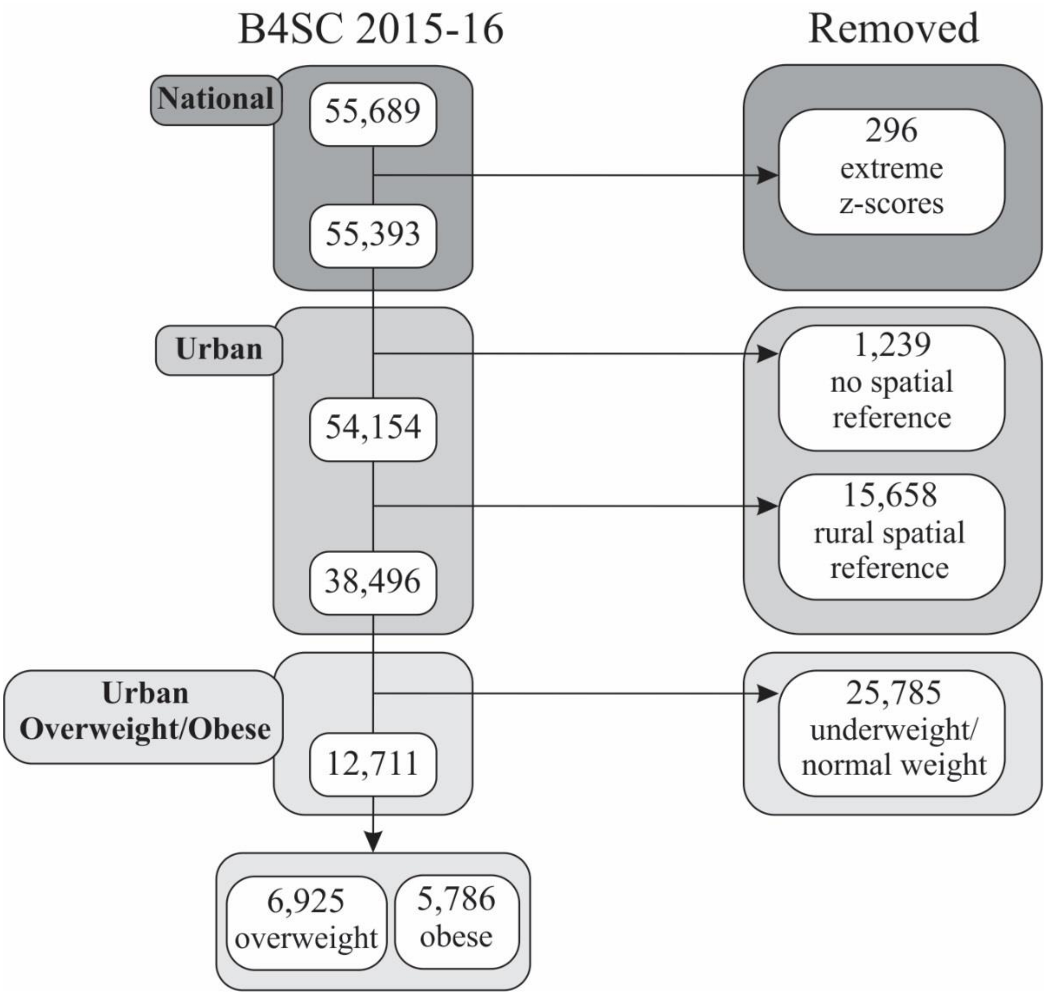

Figure E.3: *B4SC data eligibility, annual details 2015-16*

Appendix E.4

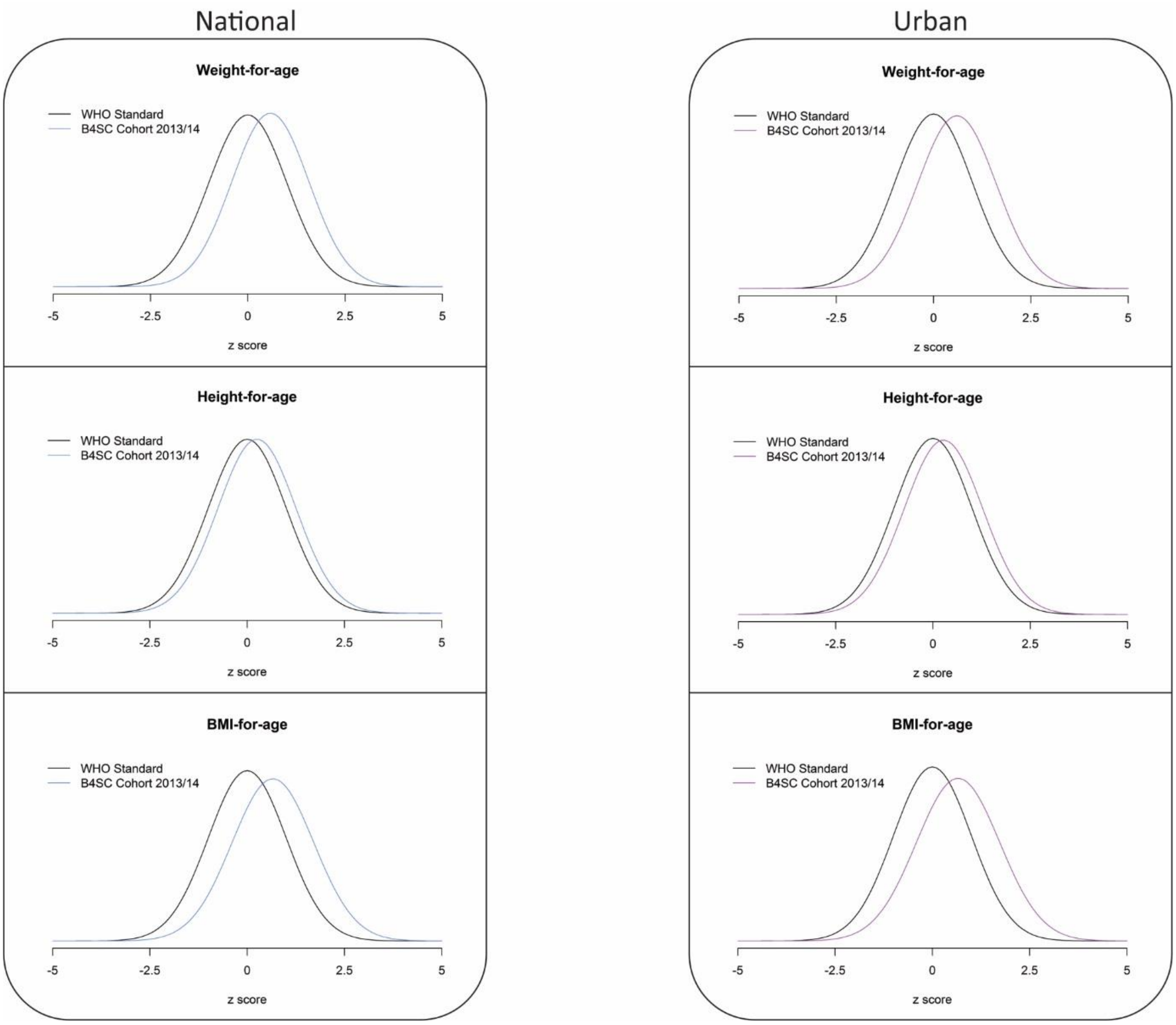

Figure E.4: *B4SC cohort (2013/14) comparisons with WHO standard, based on z-score*

Appendix E.5

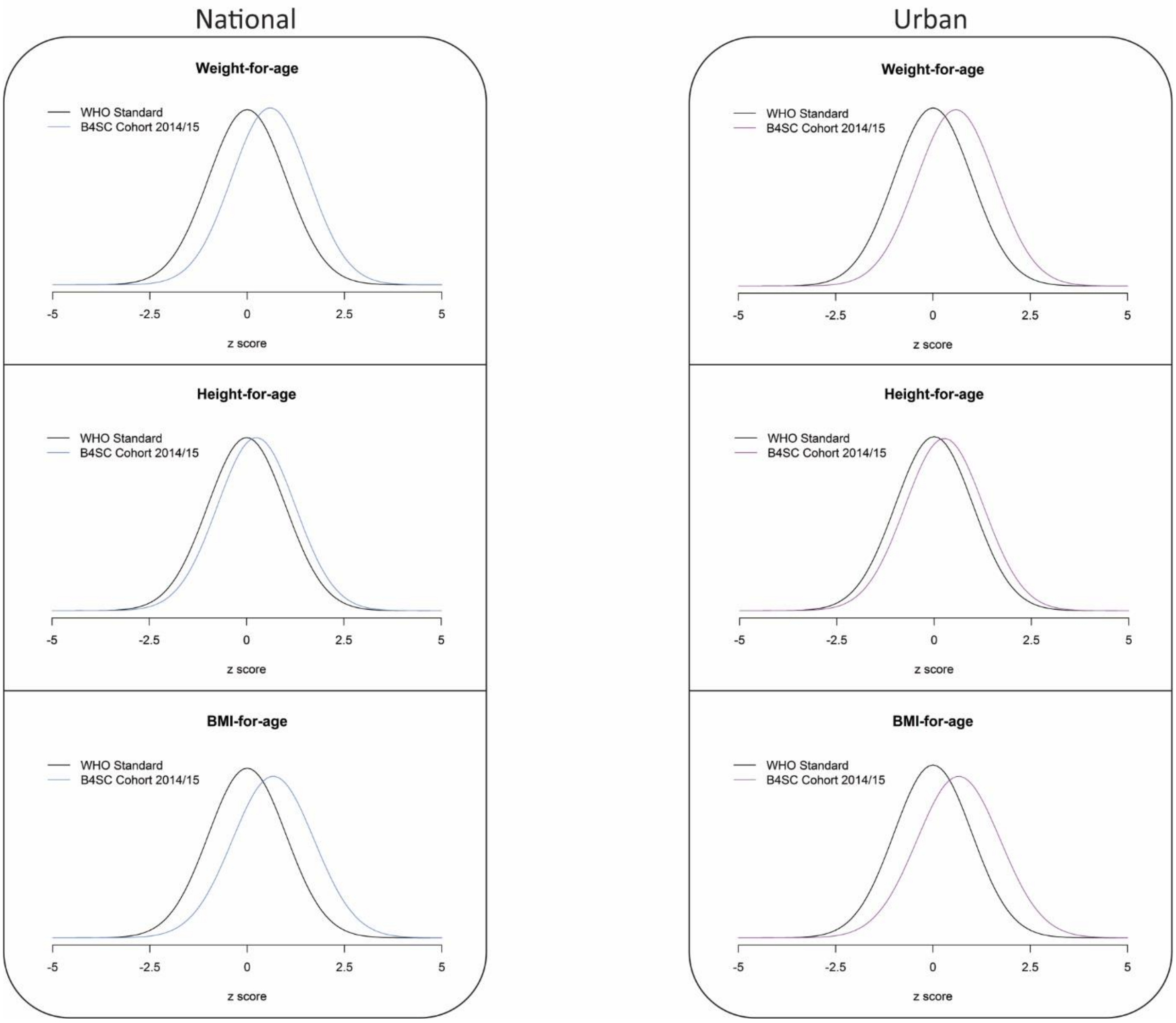

Figure E.5: *B4SC cohort (2014/15) comparisons with WHO standard, based on z-score*

Appendix E.6

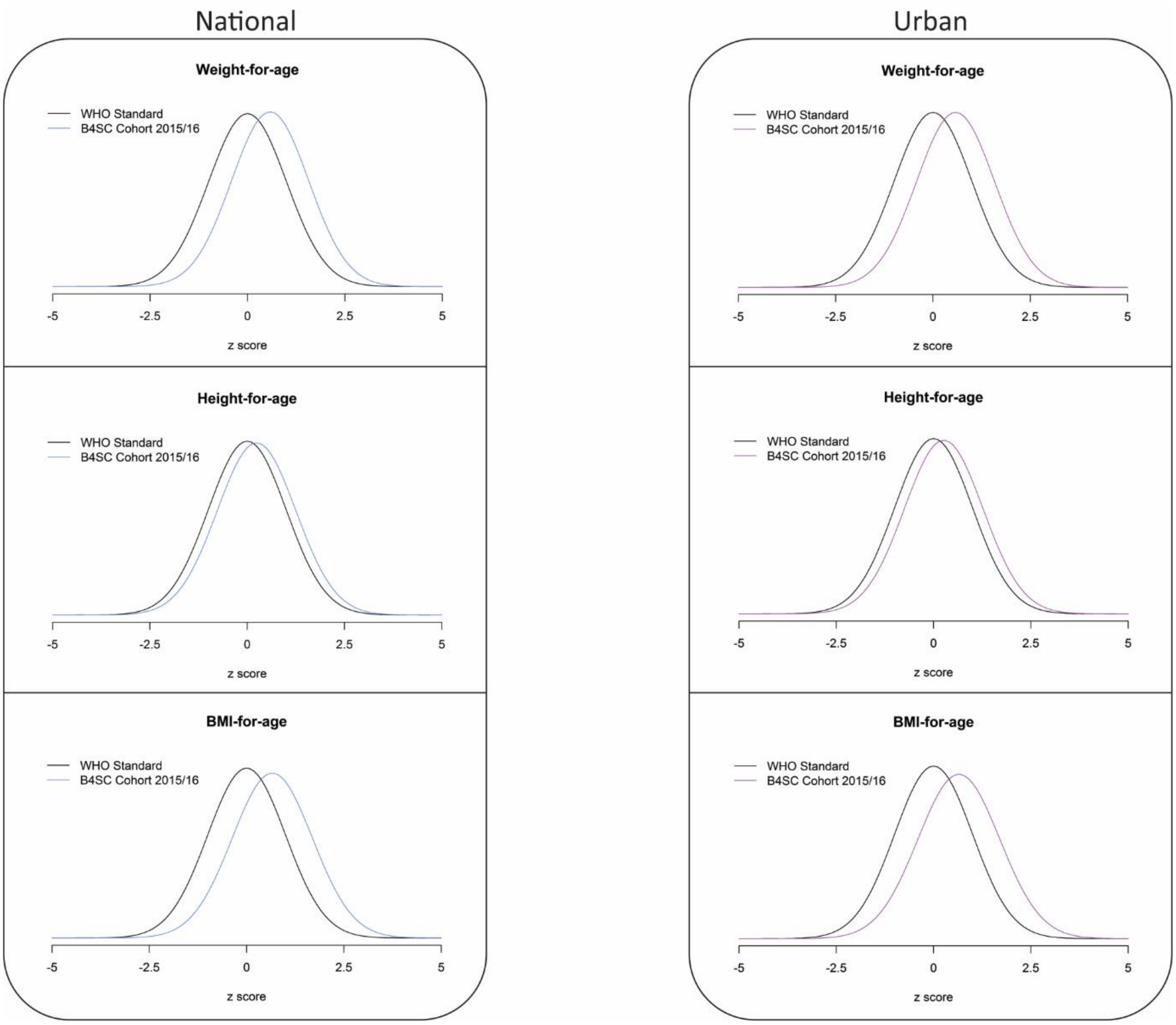

Figure E.6: *B4SC cohort (2014/15) comparisons with WHO standard, based on z-score*

Appendix E.7

Table E.1: *Logistic regression results for B4SC, by year*

	National		Urban	
	OR (95% CI)	*P*-value	OR (95% CI)	*P*-value
2013/14				
Gender				
Female	1		1	
Male	1.41 (1.36 - 1.46)	<.001	1.40 (1.34 - 1.46)	<.001
Ethnicity				
European/Other	1		1	
Māori	2.03 (1.95 - 2.12)	<.001	2.10 (1.99 - 2.21)	<.001
Pacific	3.57 (3.39 - 3.78)	<.001	3.73 (3.51 - 3.95)	<.001
2014/15				
Gender				
Female	1		1	
Male	1.37 (1.32 - 1.42)	<.001	1.35 (1.30 - 1.41)	<.001
Ethnicity				
European/Other	1		1	
Māori	2.01 (1.93 - 2.09)	<.001	2.09 (1.99 - 2.20)	<.001
Pacific	3.45 (3.27 - 3.63)	<.001	3.65 (3.45 - 3.87)	<.001
2015/16				
Gender				
Female	1		1	
Male	1.39 (1.34 - 1.44)	<.001	1.38 (1.32 - 1.44)	<.001
Ethnicity				
European/Other	1		1	
Māori	2.03 (1.95 - 2.12)	<.001	2.16 (2.05 - 2.27)	<.001
Pacific	3.27 (3.10 - 3.45)	<.001	3.54 (3.34 - 3.75)	<.001

Appendix E.8

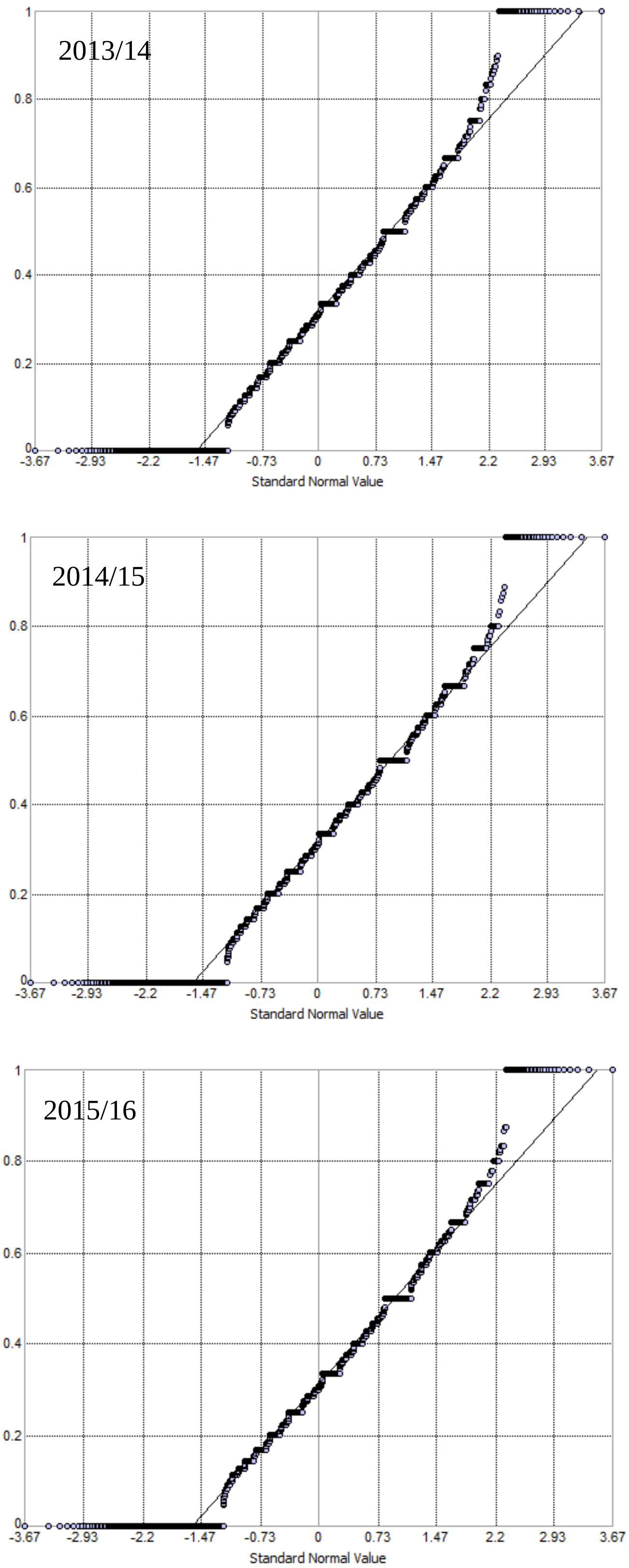

Figure E.7: *QQ plot of normality for high weight status in 4 – 5 year old children as a crude rate per 1,000 population for the years 2013/14, 2014/15, and 2015/16*

Appendix E.9

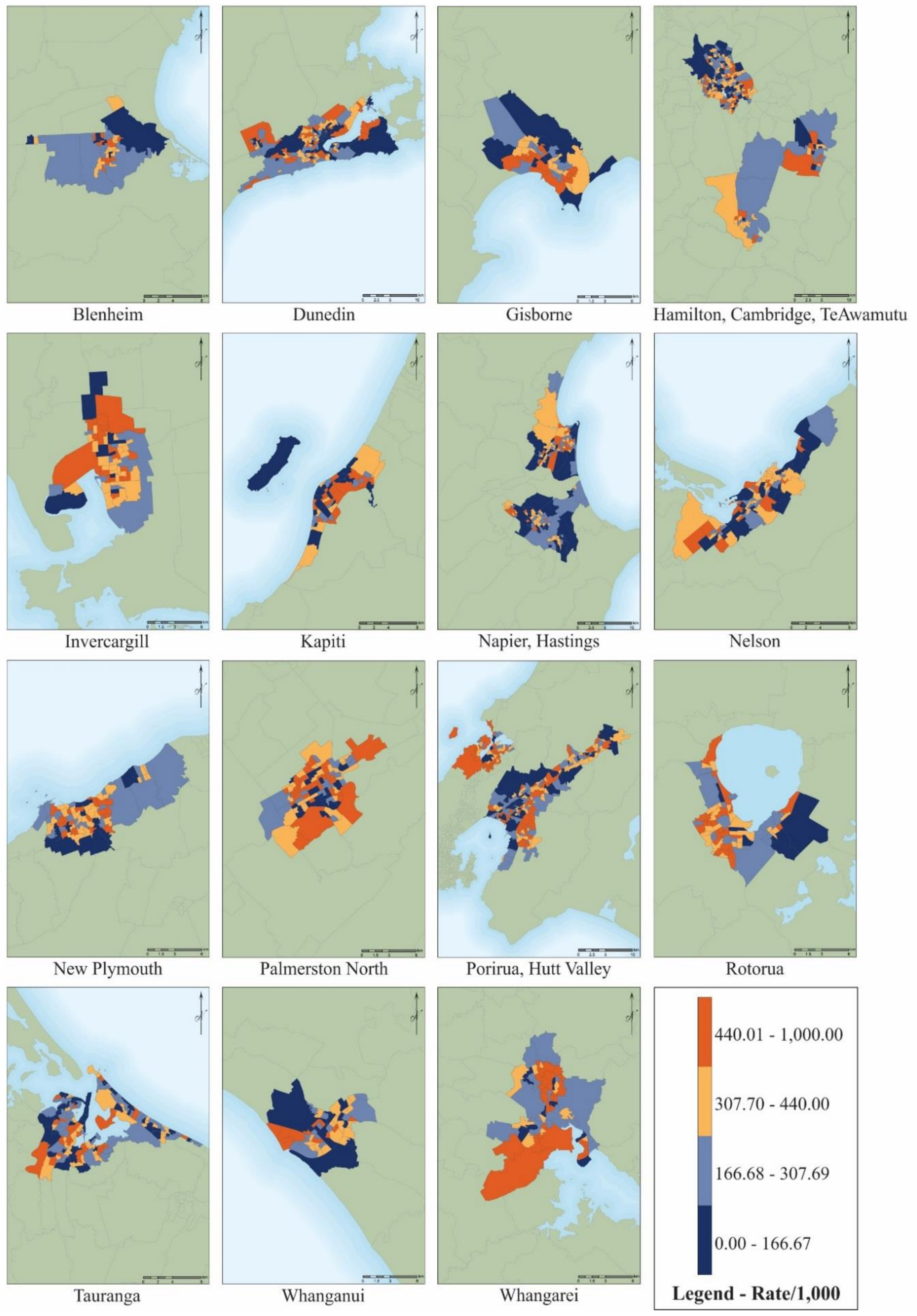

Figure E.8: *Rate of high weight status in 4–5 year old children per 1,000 population 2013/14*

Appendix E.10

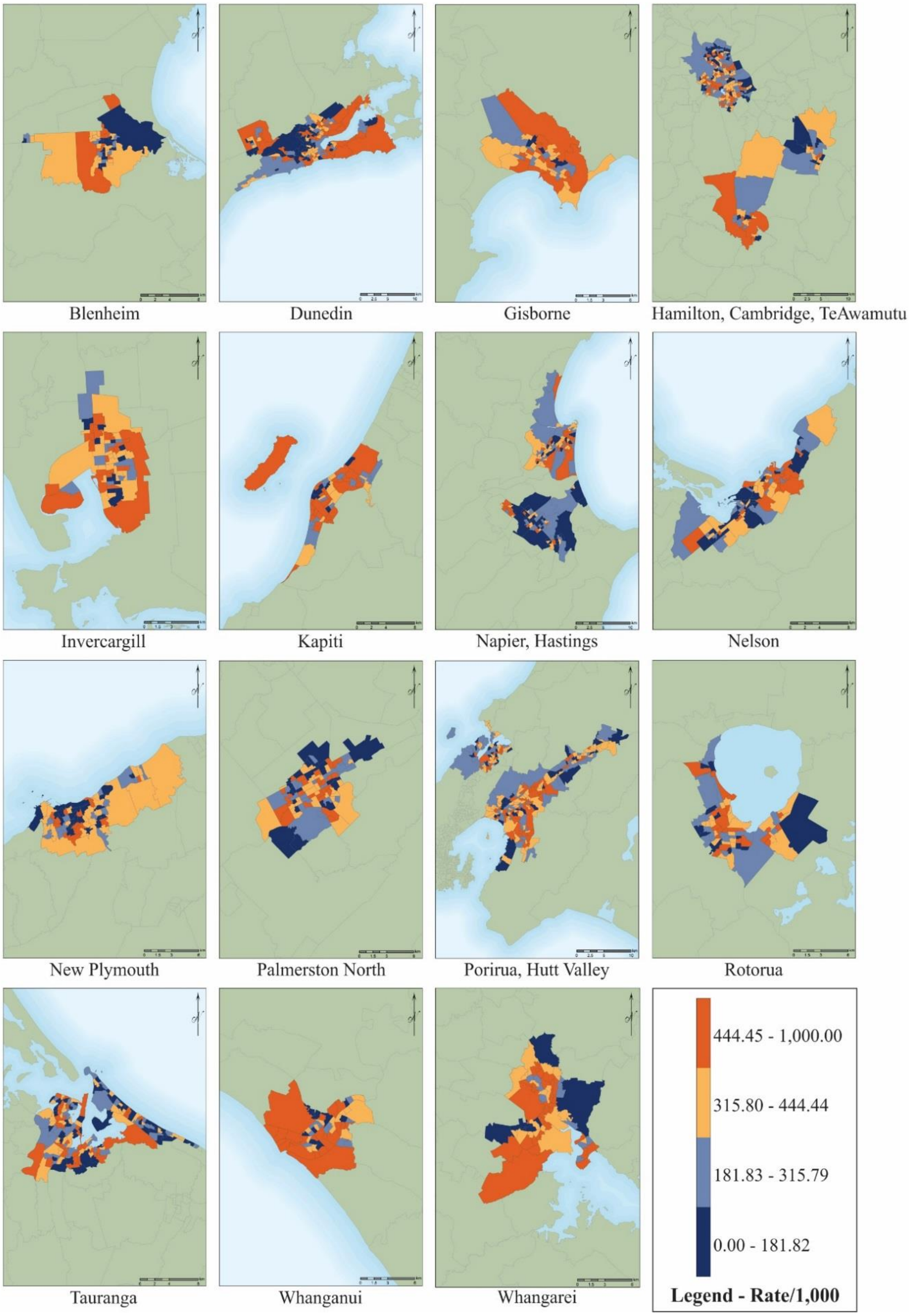

Figure E.9: *Rate of high weight status in 4–5 year old children per 1,000 population 2014/15*

Appendix E.11

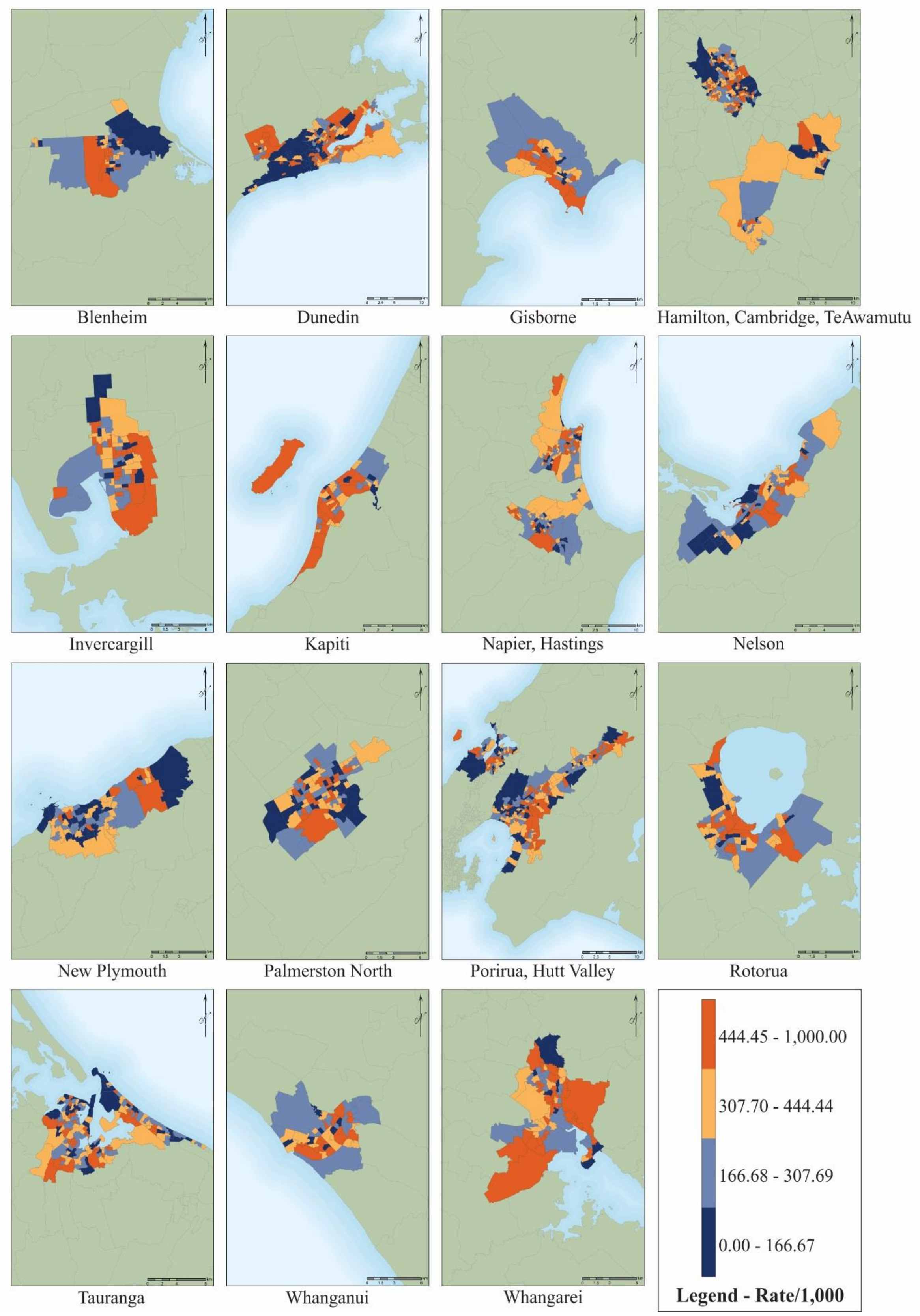

Figure E.10: *Rate of high weight status in 4–5 year old children per 1,000 population 2015/16*

Appendix E.12

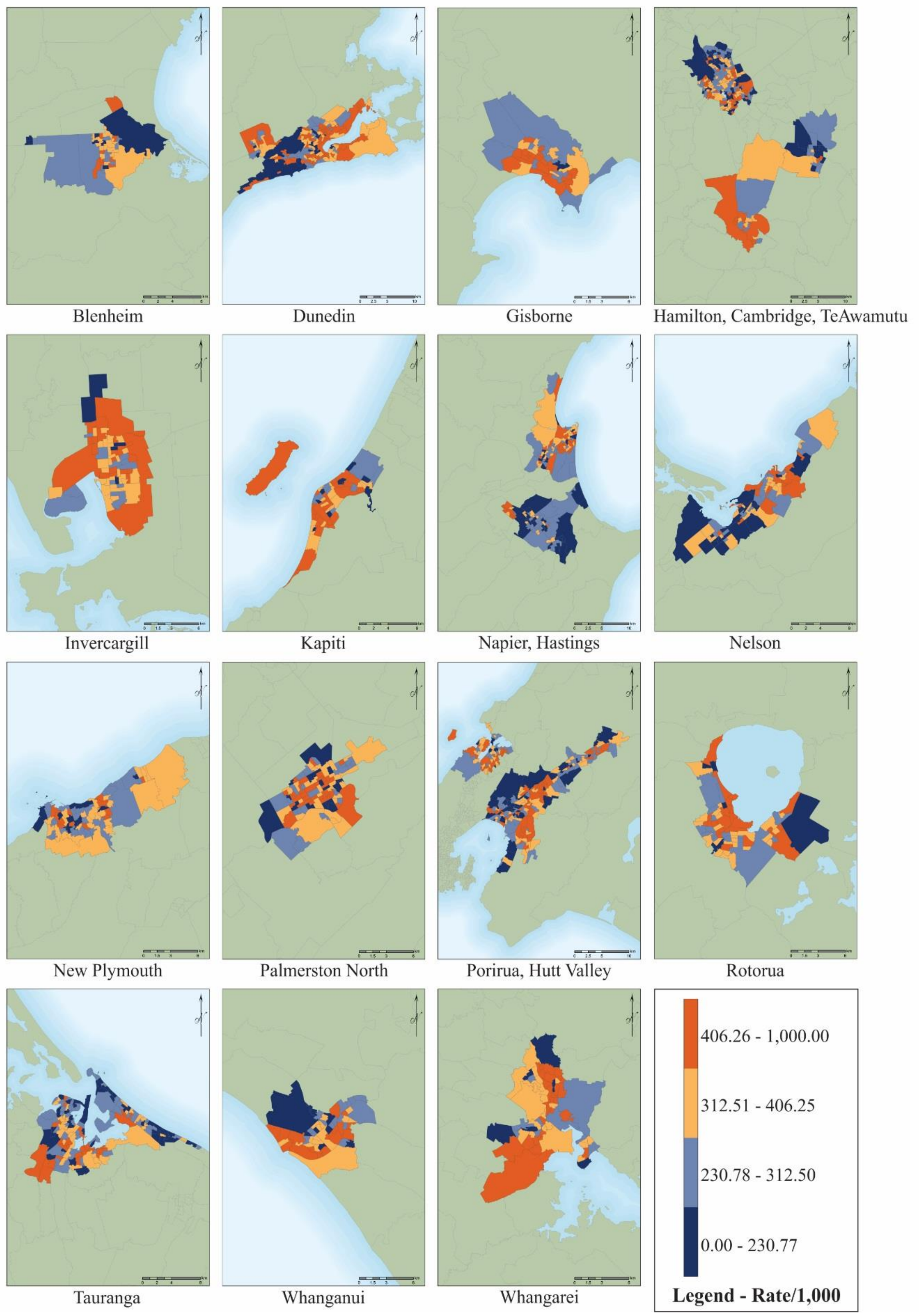

Figure E.11: *Rate of high weight status in 4–5 year old children per 1,000 population 2013/16*

Appendix E.13

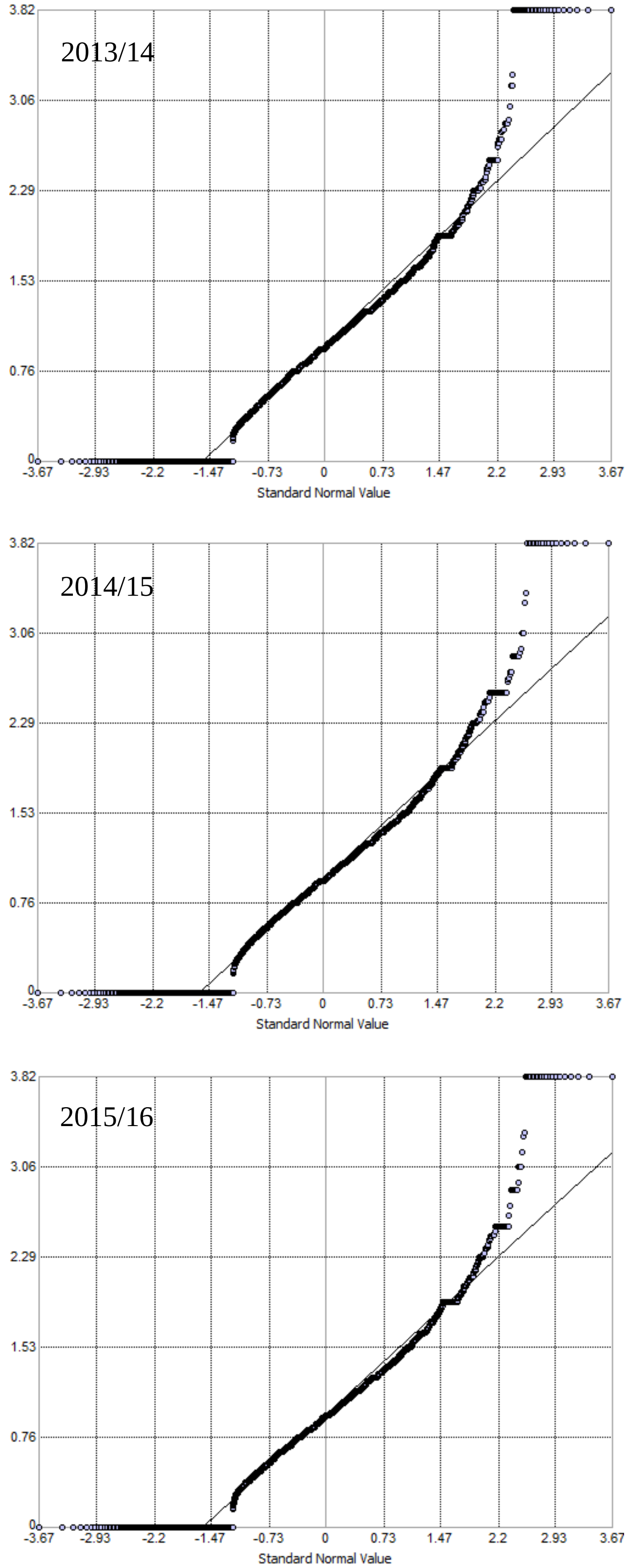

Figure E.12: *QQ plot of normality for SMR of high weight status in 4 – 5 year old children for the years 2013/14, 2014/15, and 2015/16*

Appendix E.14

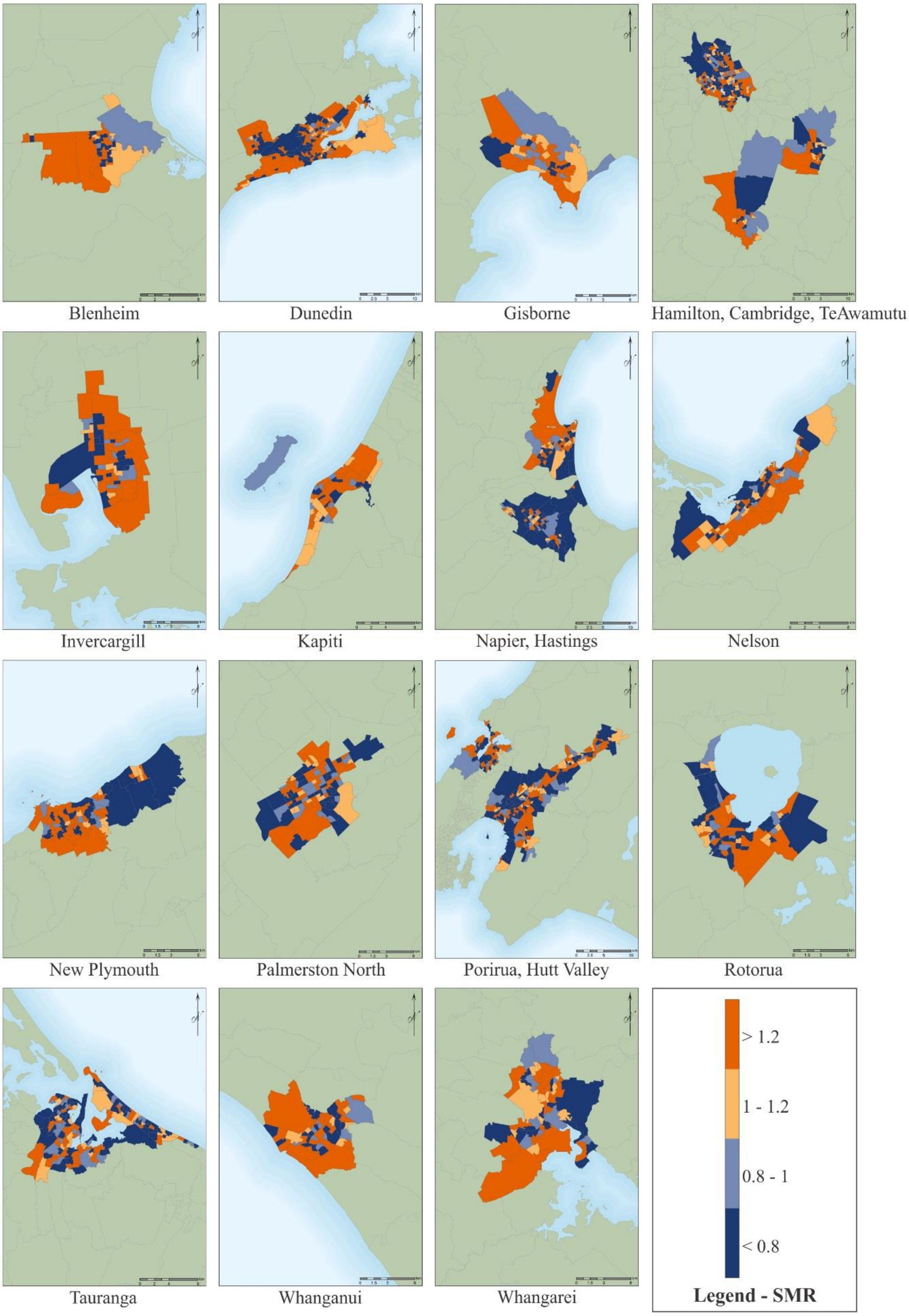

Figure E.13: *SMR of high weight status in 4–5 year old children, 2013/14*

Appendix E.15

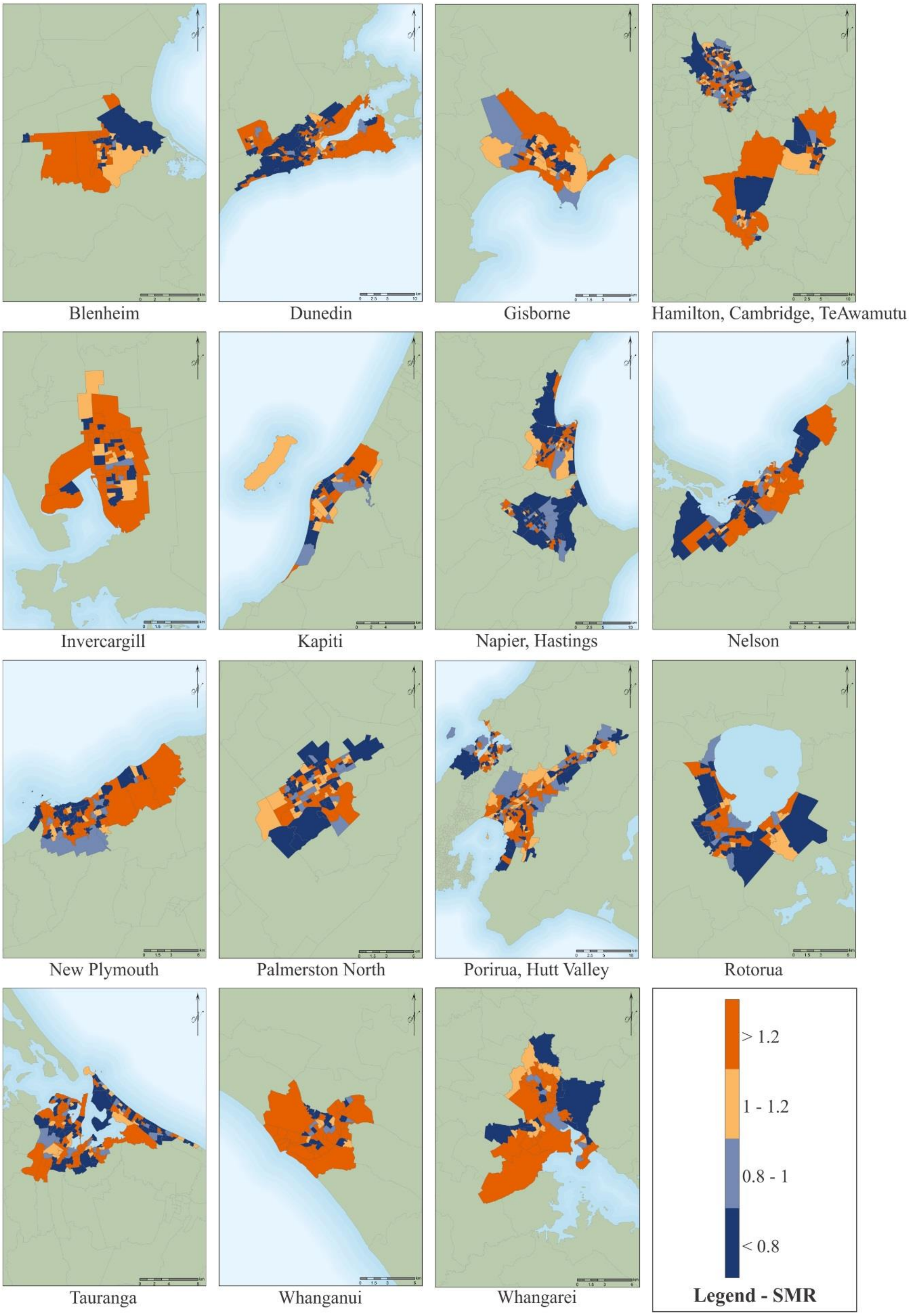

Figure E.14: *SMR of high weight status in 4–5 year old children, 2014/15*

Appendix E.16

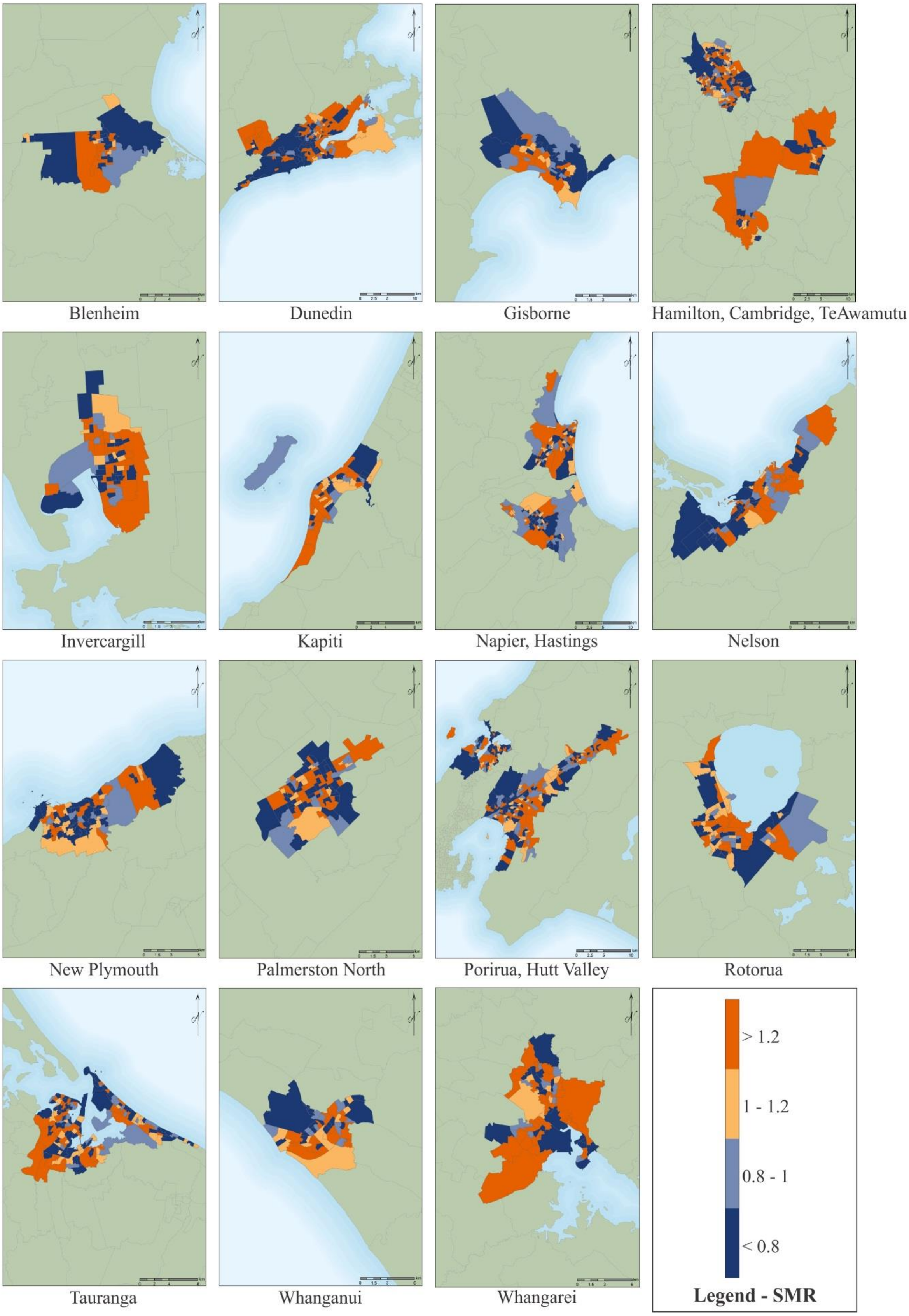

Figure E.15: *SMR of high weight status in 4–5 year old children, 2015/16*

Appendix E.17

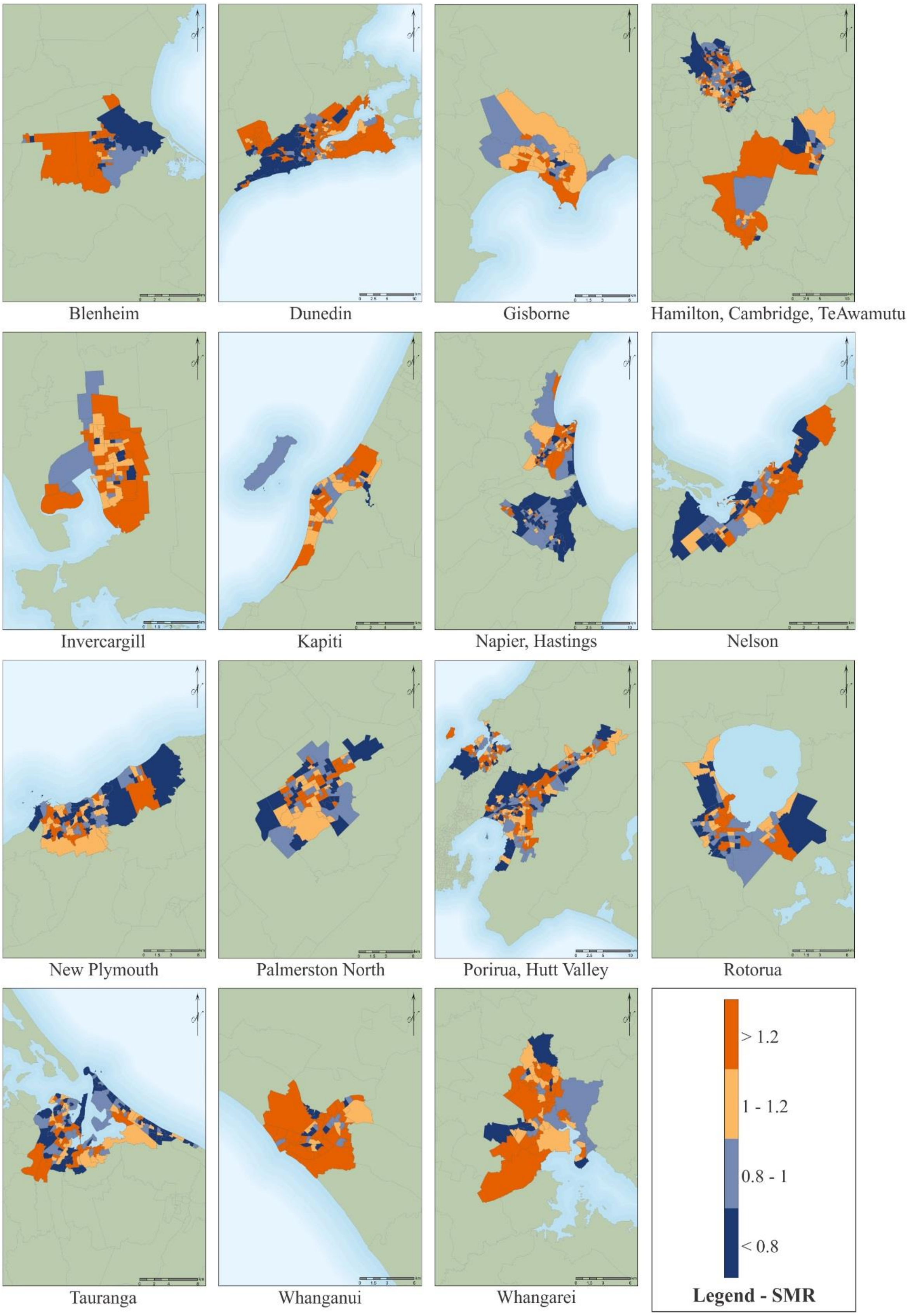

Figure E.16: *Average SMR of high weight status in 4–5 year old children, 2013/16*

Appendix E.18

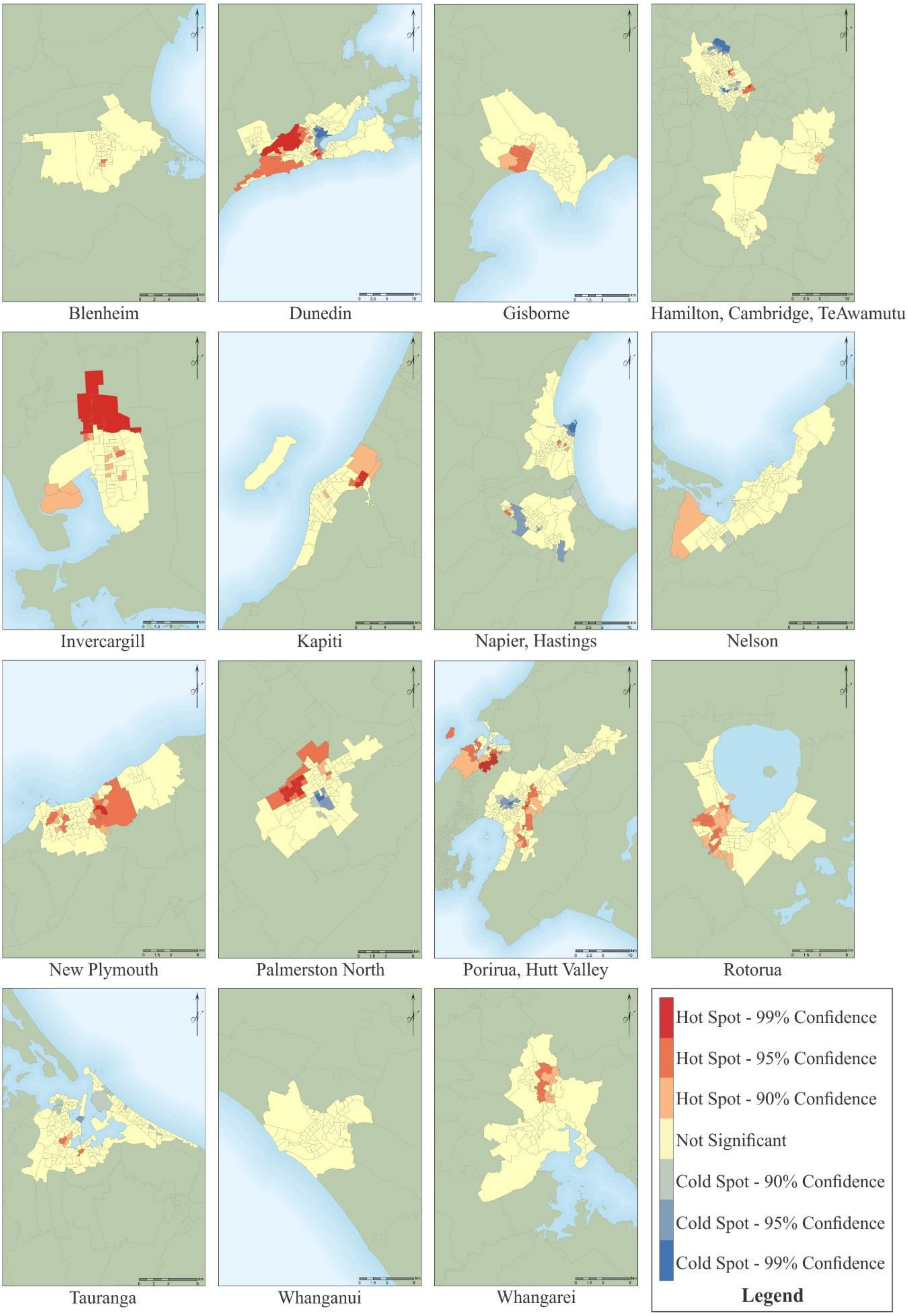

Figure E.17: *Other urban areas – Local clustering (2013/14 Rate per 1,000)*

Appendix E.19

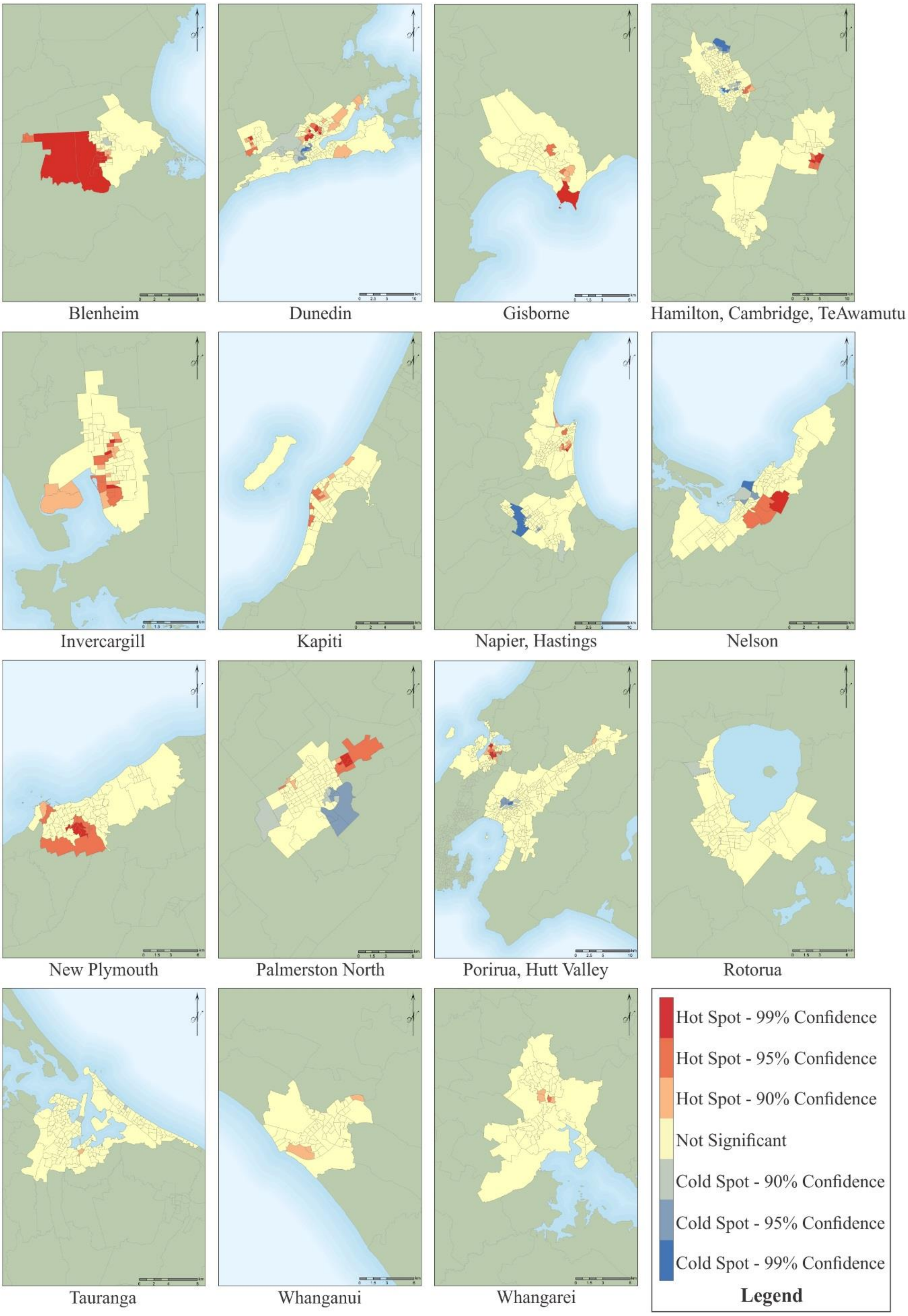

Figure E.18: *Other urban areas – Local clustering (2013/14 SMR)*

Appendix E.20

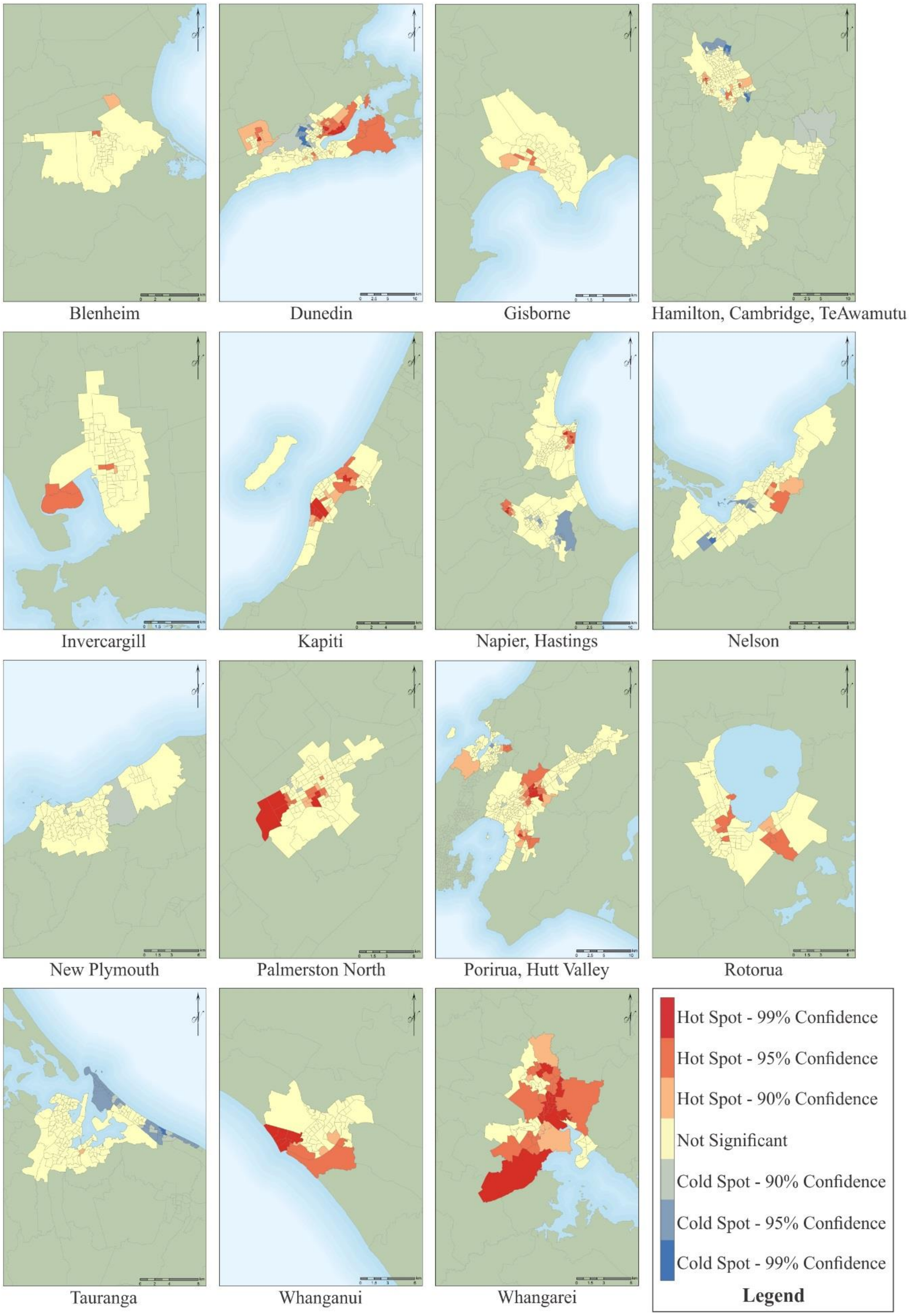

Figure E.19: *Other urban areas – Local clustering (2014/15 Rate per 1,000)*

Appendix E.21

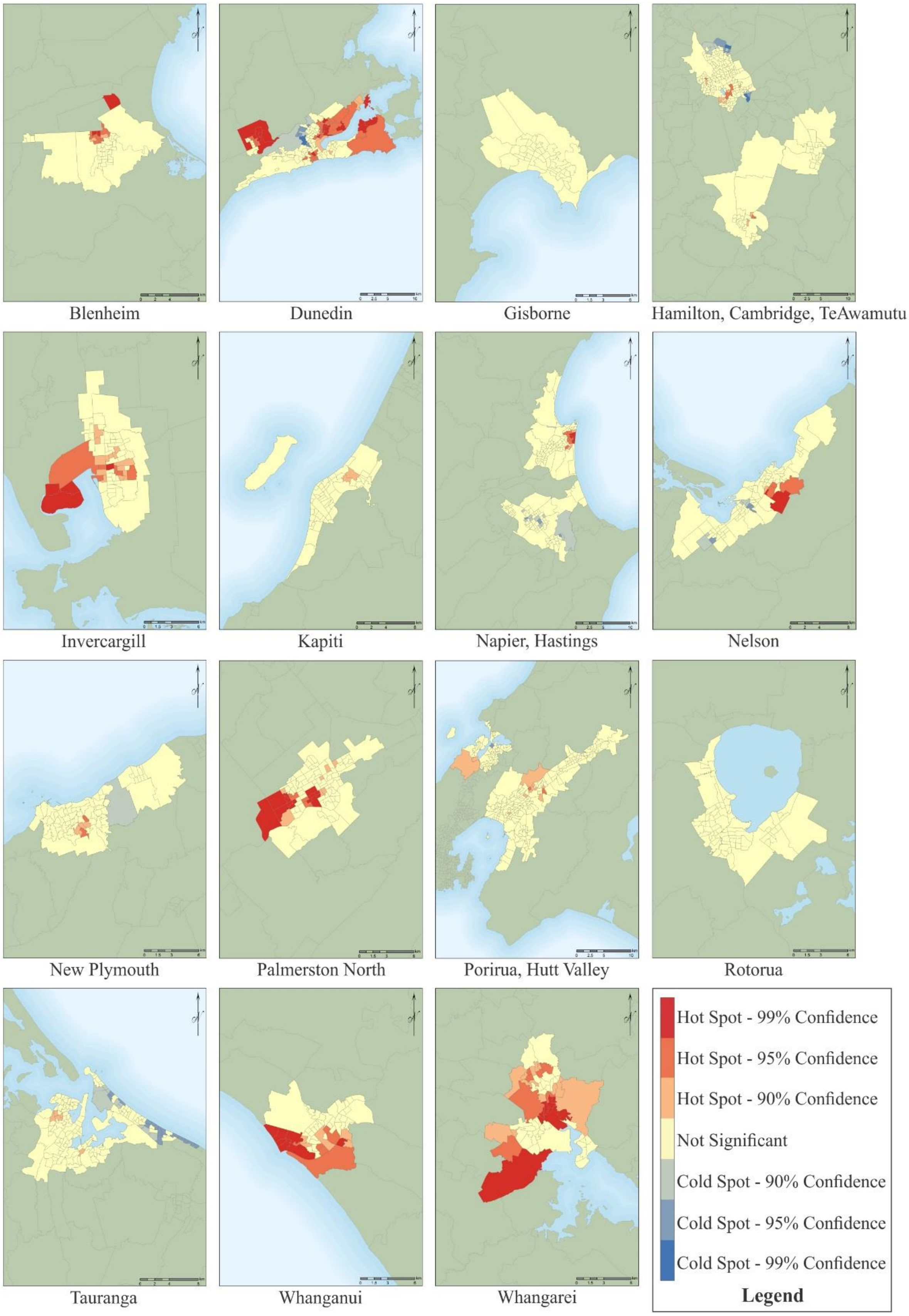

Figure E.20: *Other urban areas – Local clustering (2014/15 SMR)*

Appendix E.22

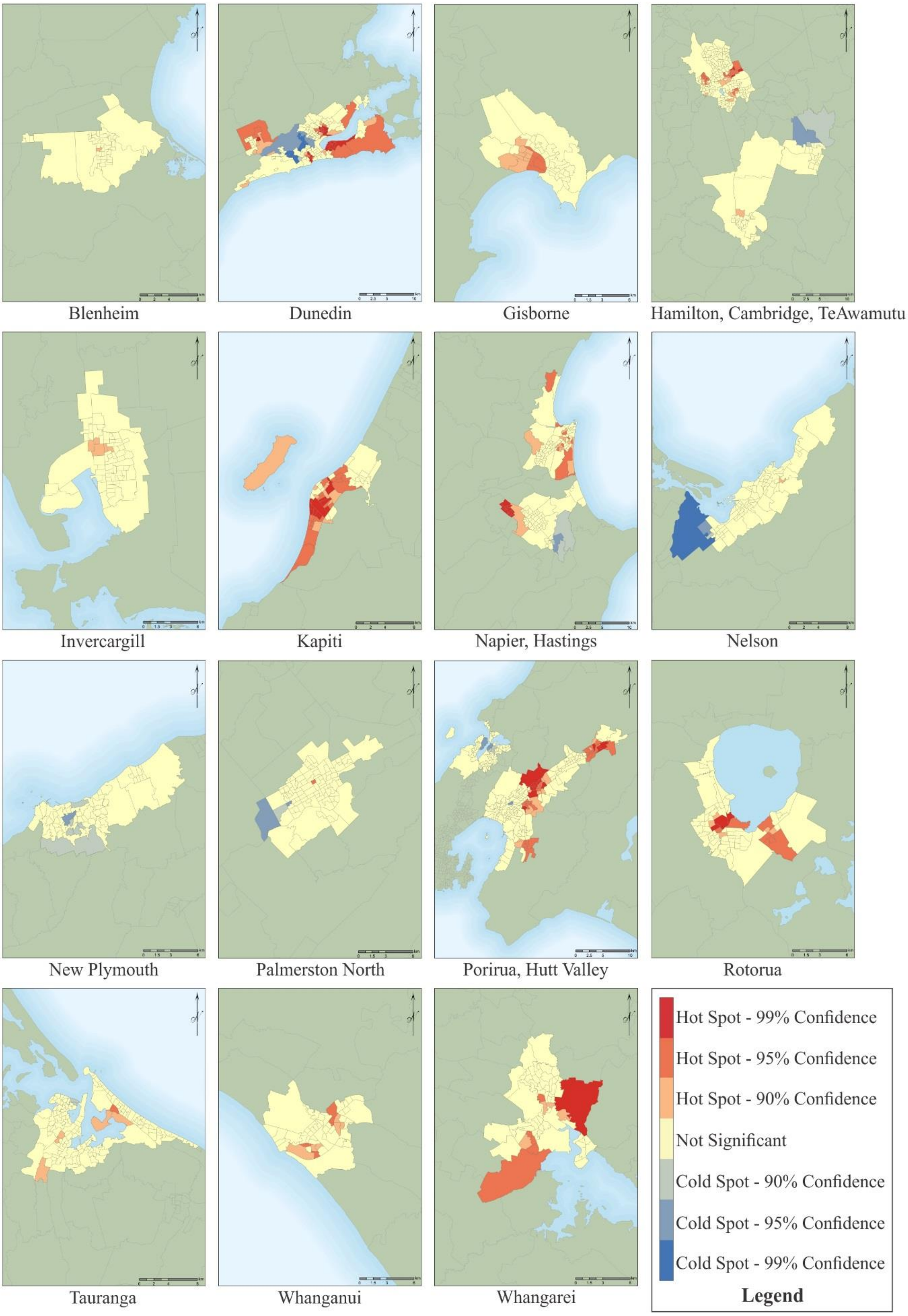

Figure E.21: *Other urban areas – Local clustering (2015/16 Rate per 1,000)*

Appendix E.23

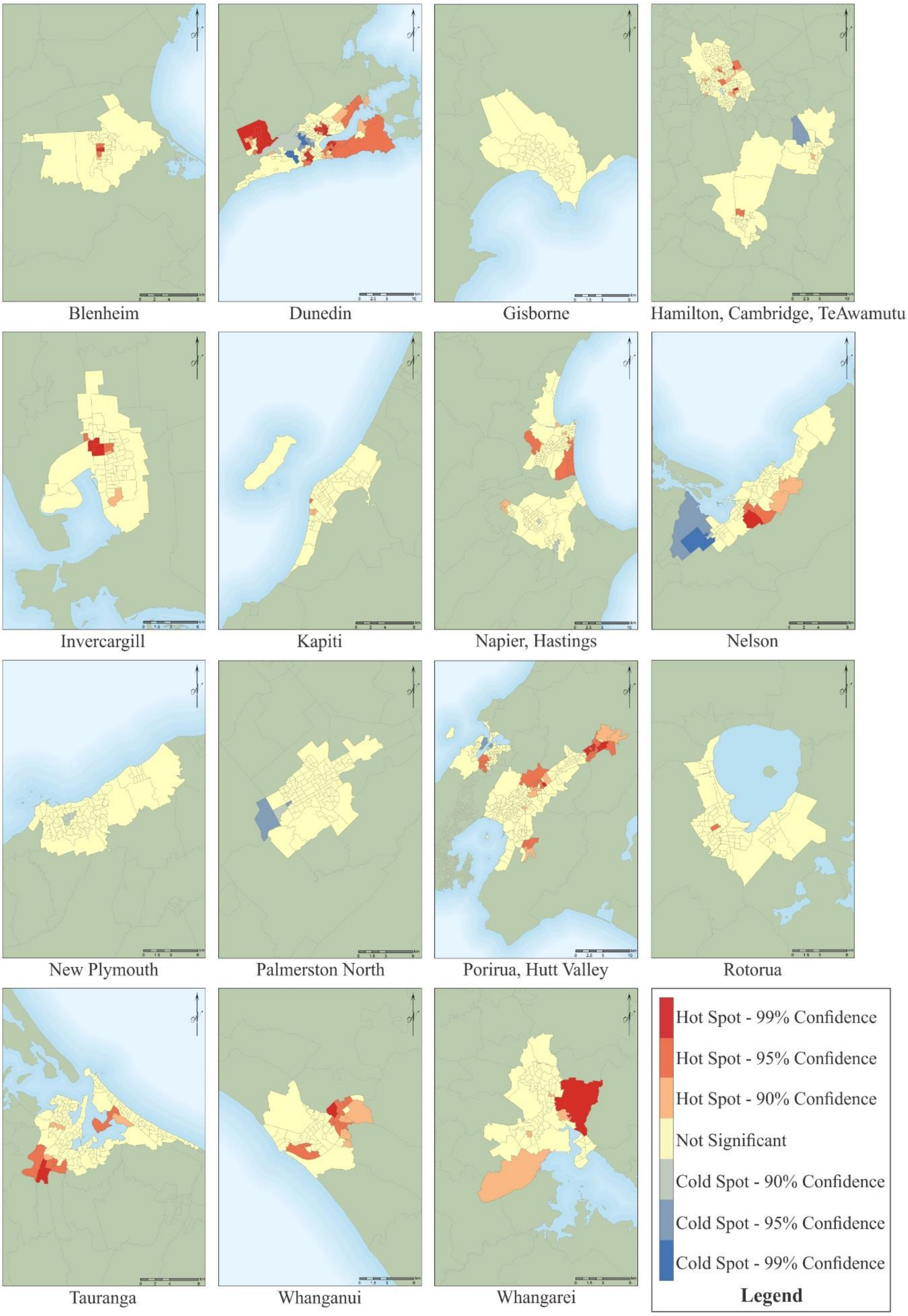

Figure E.22: *Other urban areas – Local clustering (2015/16 SMR)*

Appendix E.24

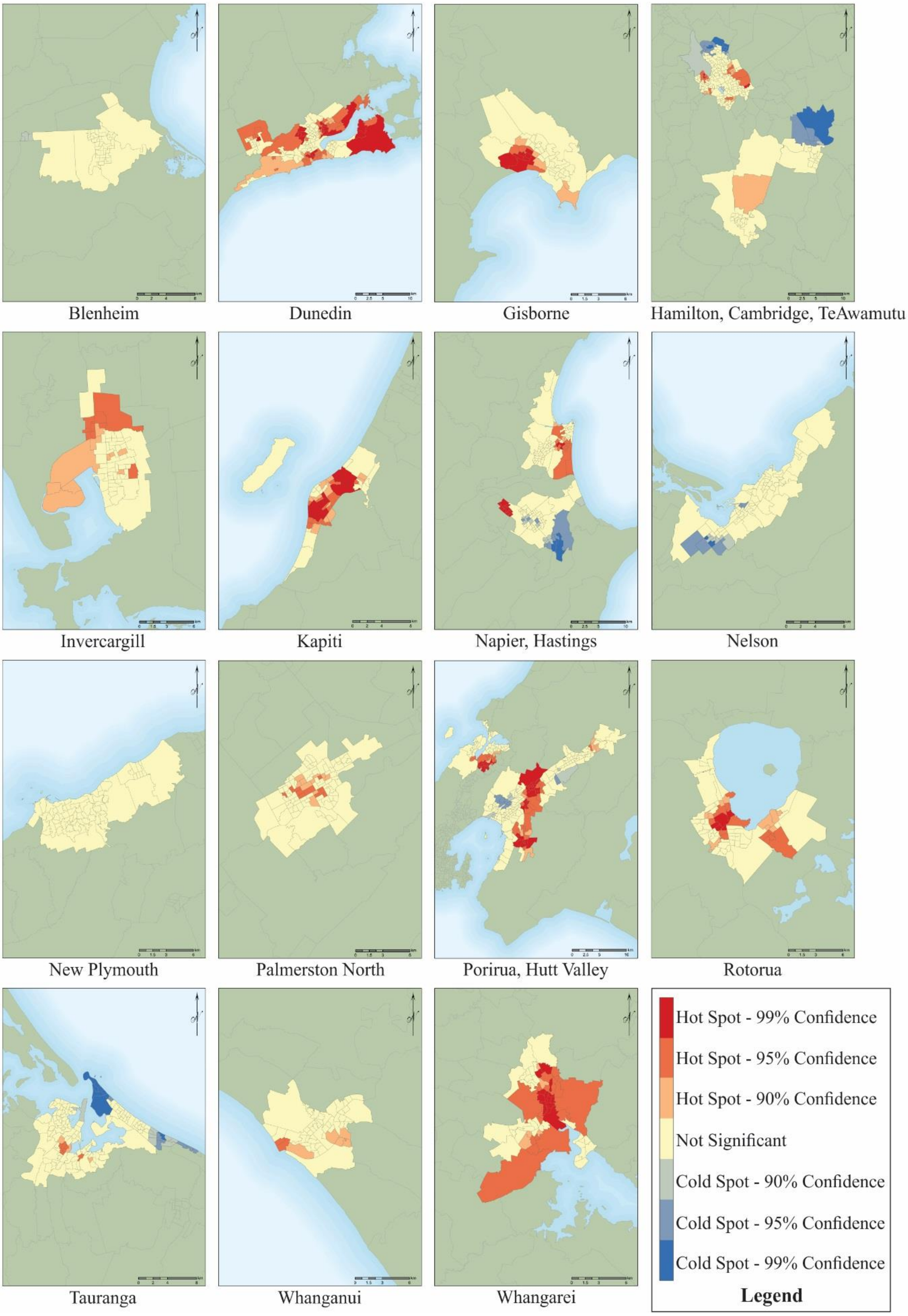

Figure E.23: *Other urban areas – Local clustering (2013/16 Rate per 1,000)*

Appendix E.25

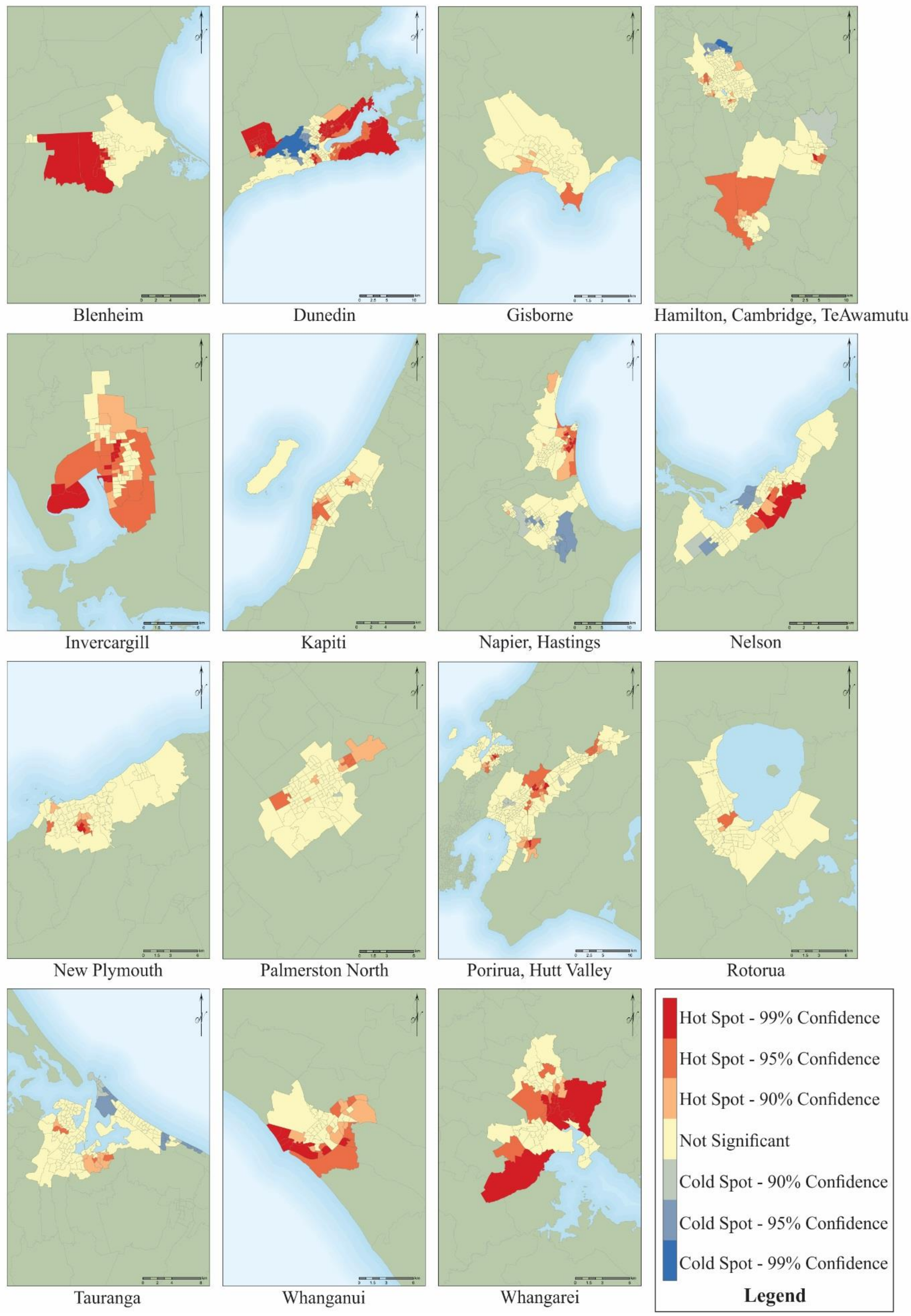

Figure E.24: *Other urban areas – Local clustering (2013/16 SMR)*

Appendix E.26

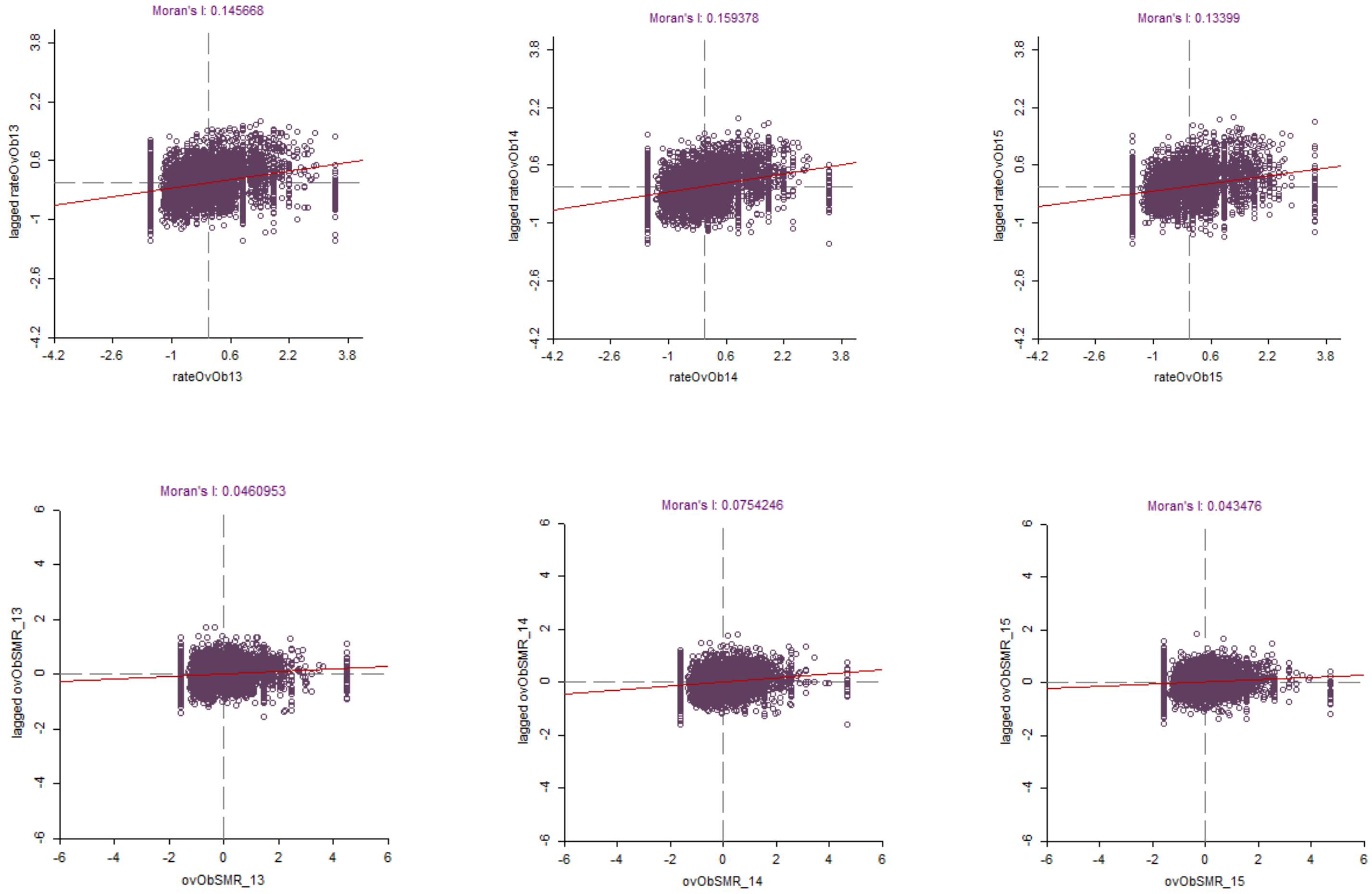

Figure E.25: *Moran's I scatterplot for high weight status in 4 – 5 year old children as a crude rate per 1,000 (upper) and SMR (lower) for the years 2013/14 (left), 2014/15 (centre), and 2015/16 (right)*

Appendix E.27

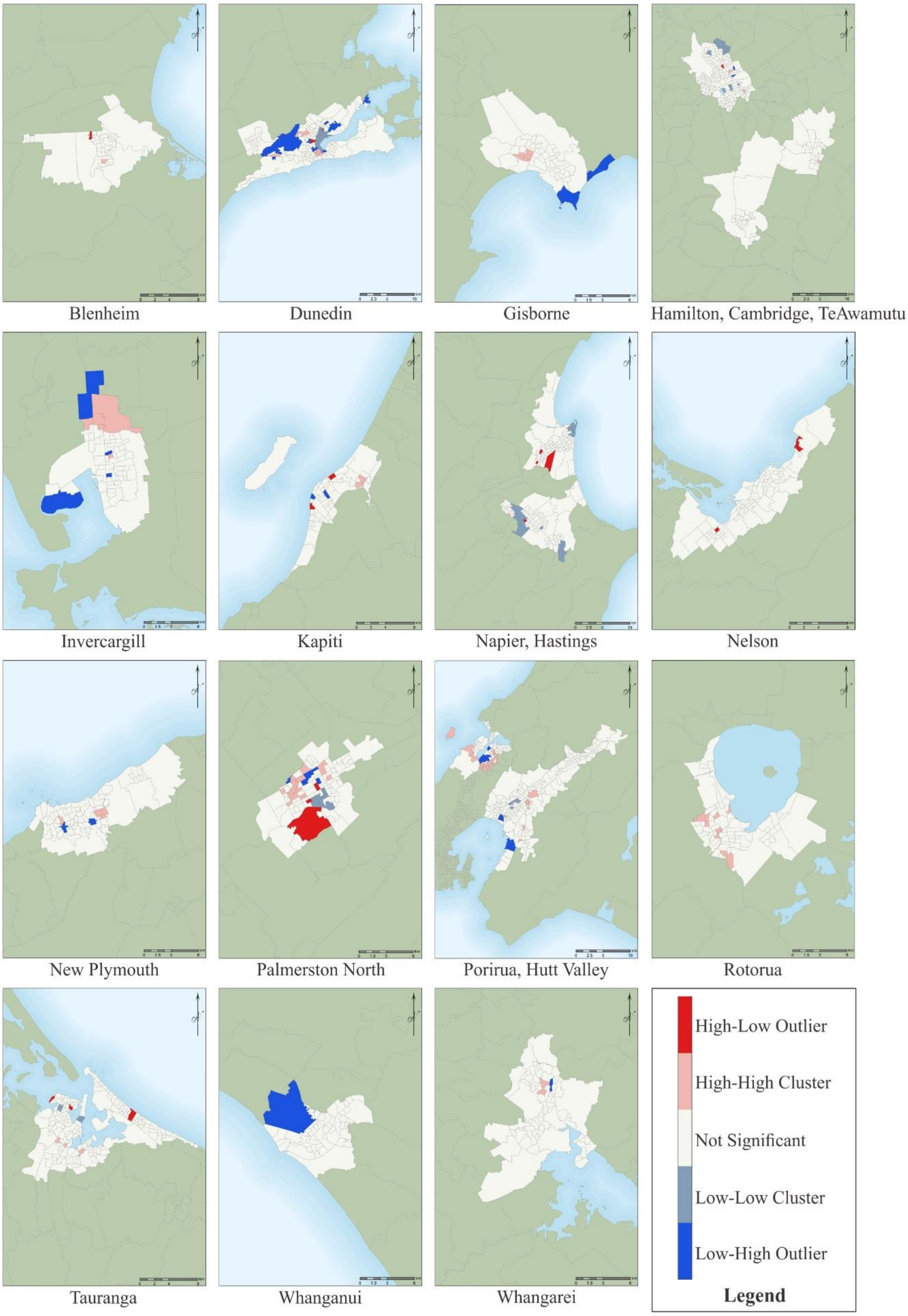

Figure E.26: *Other urban areas – Local spatial autocorrelation (2013/14 Rate per 1,000)*

Appendix E.28

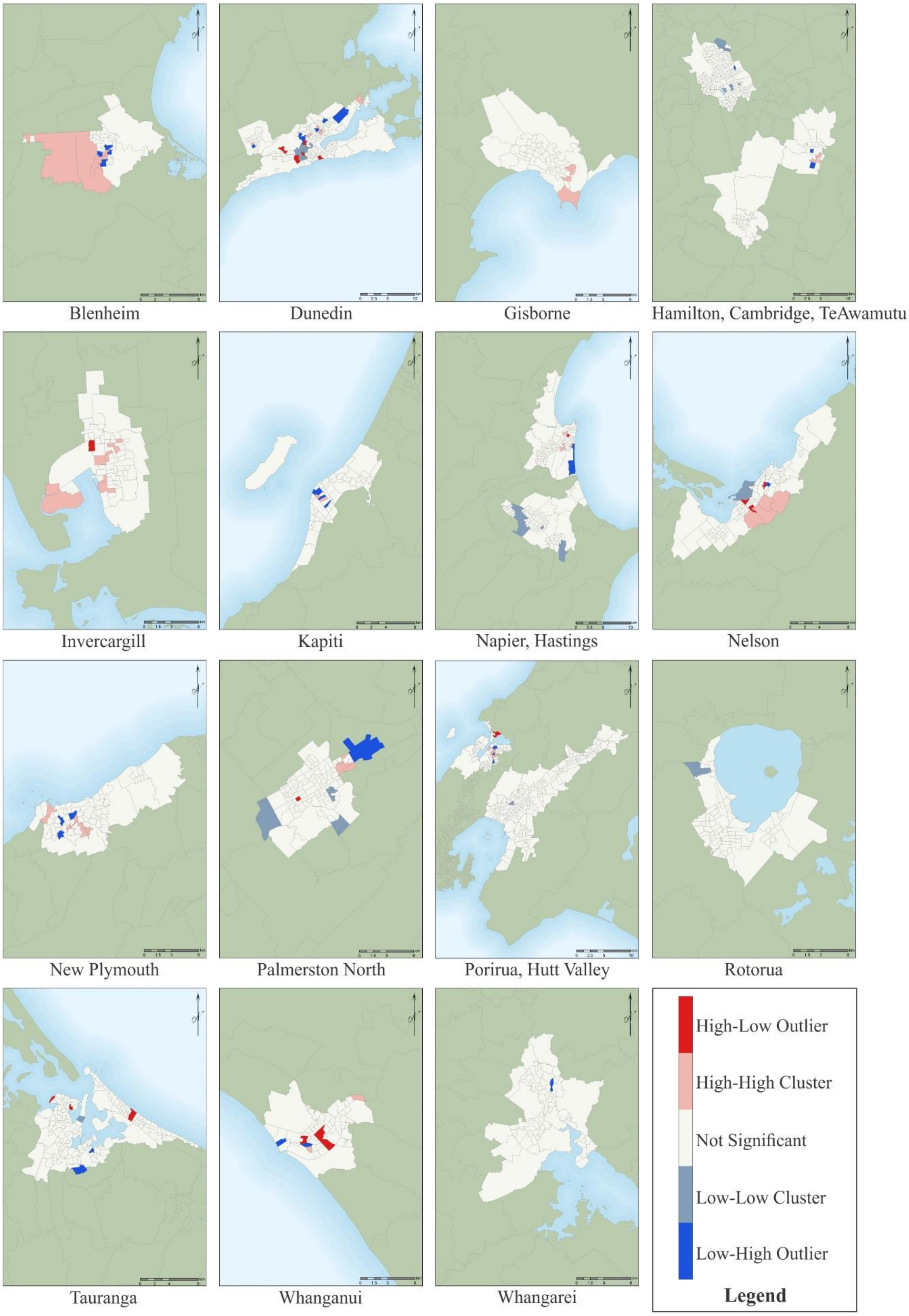

Figure E.27: *Other urban areas – Local spatial autocorrelation (2013/14 SMR)*

Appendix E.29

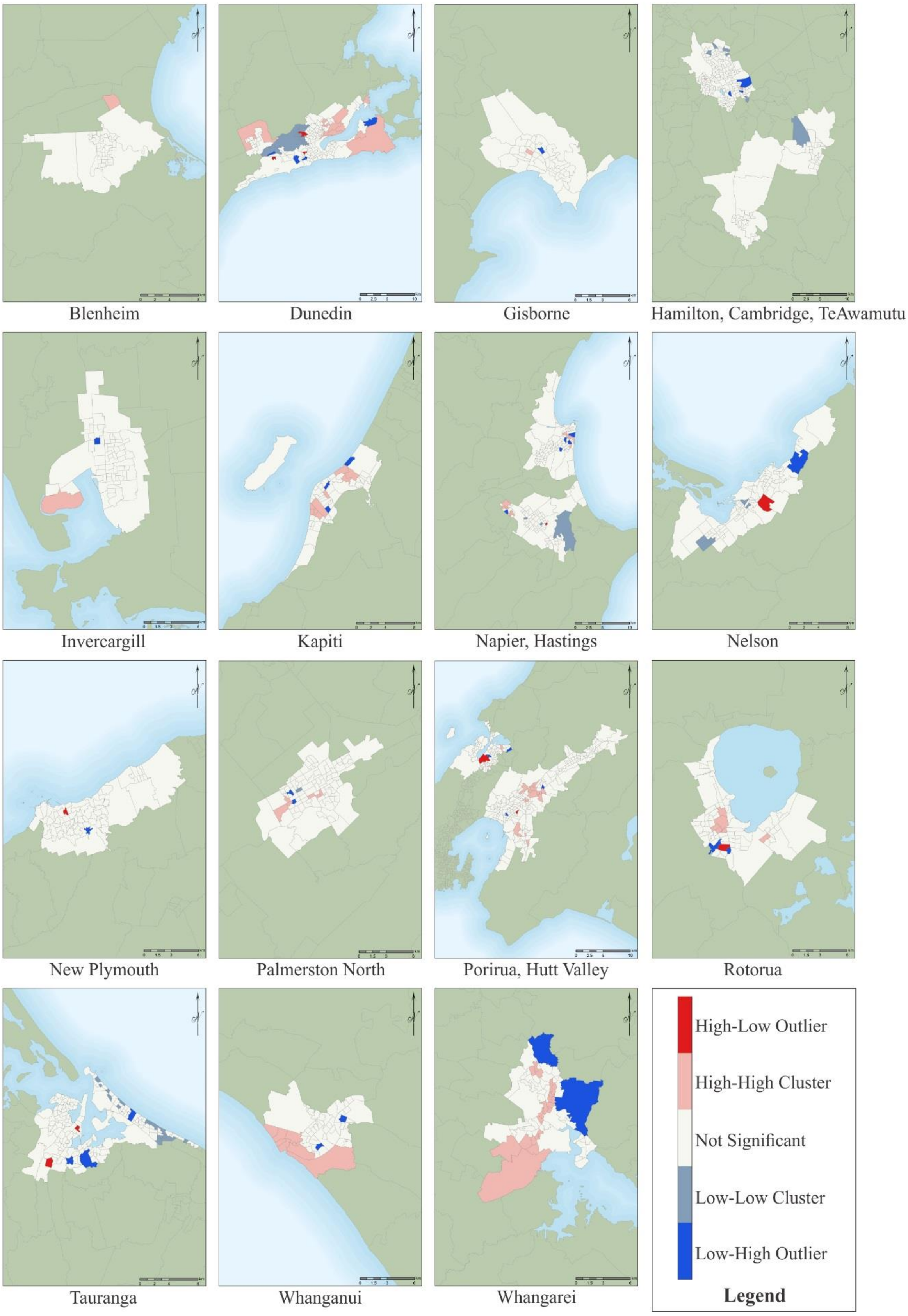

Figure E.28: *Other urban areas – Local spatial autocorrelation (2014/15 Rate per 1,000)*

Appendix E.30

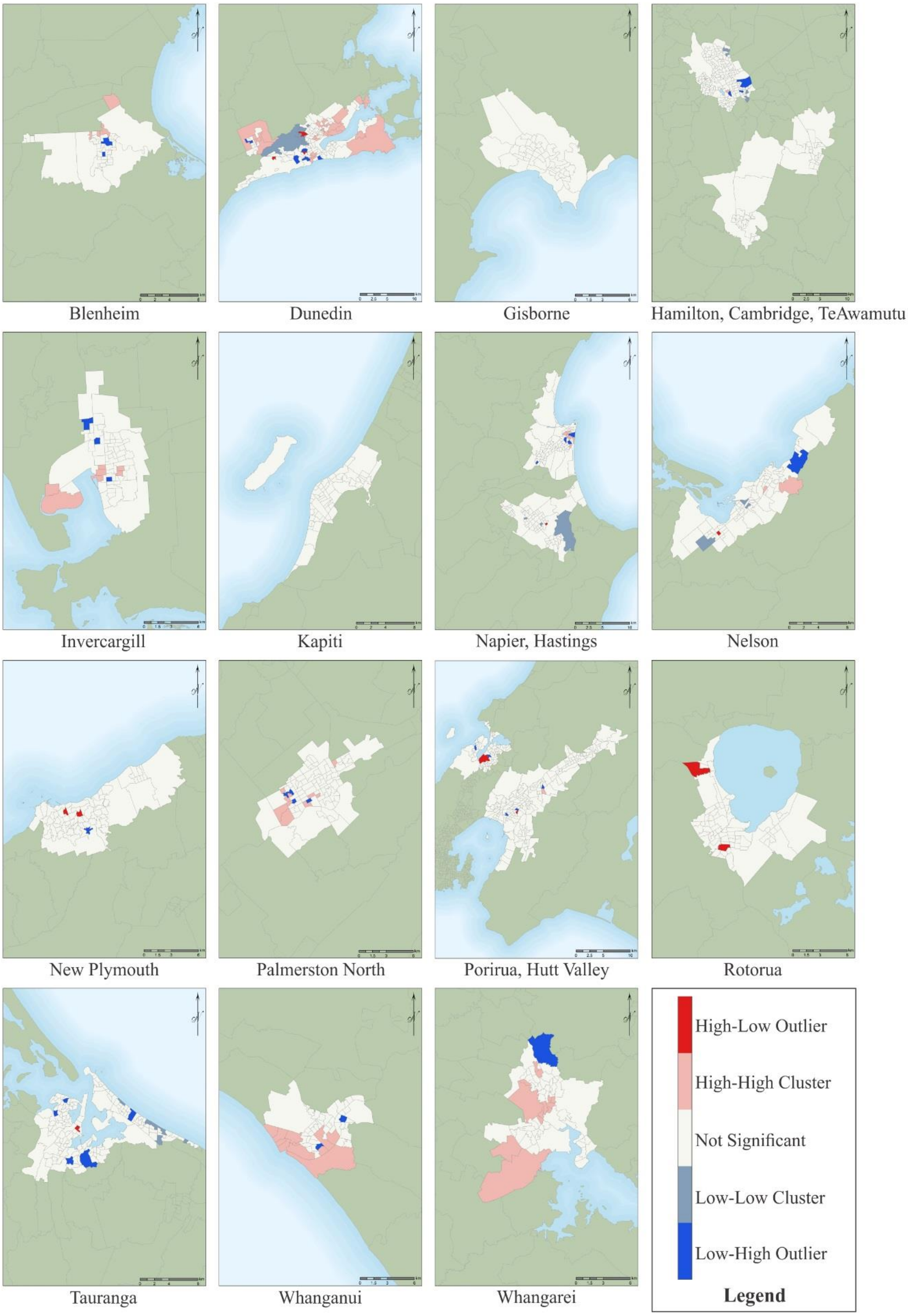

Figure E.29: *Other urban areas – Local spatial autocorrelation (2014/15 SMR)*

Appendix E.31

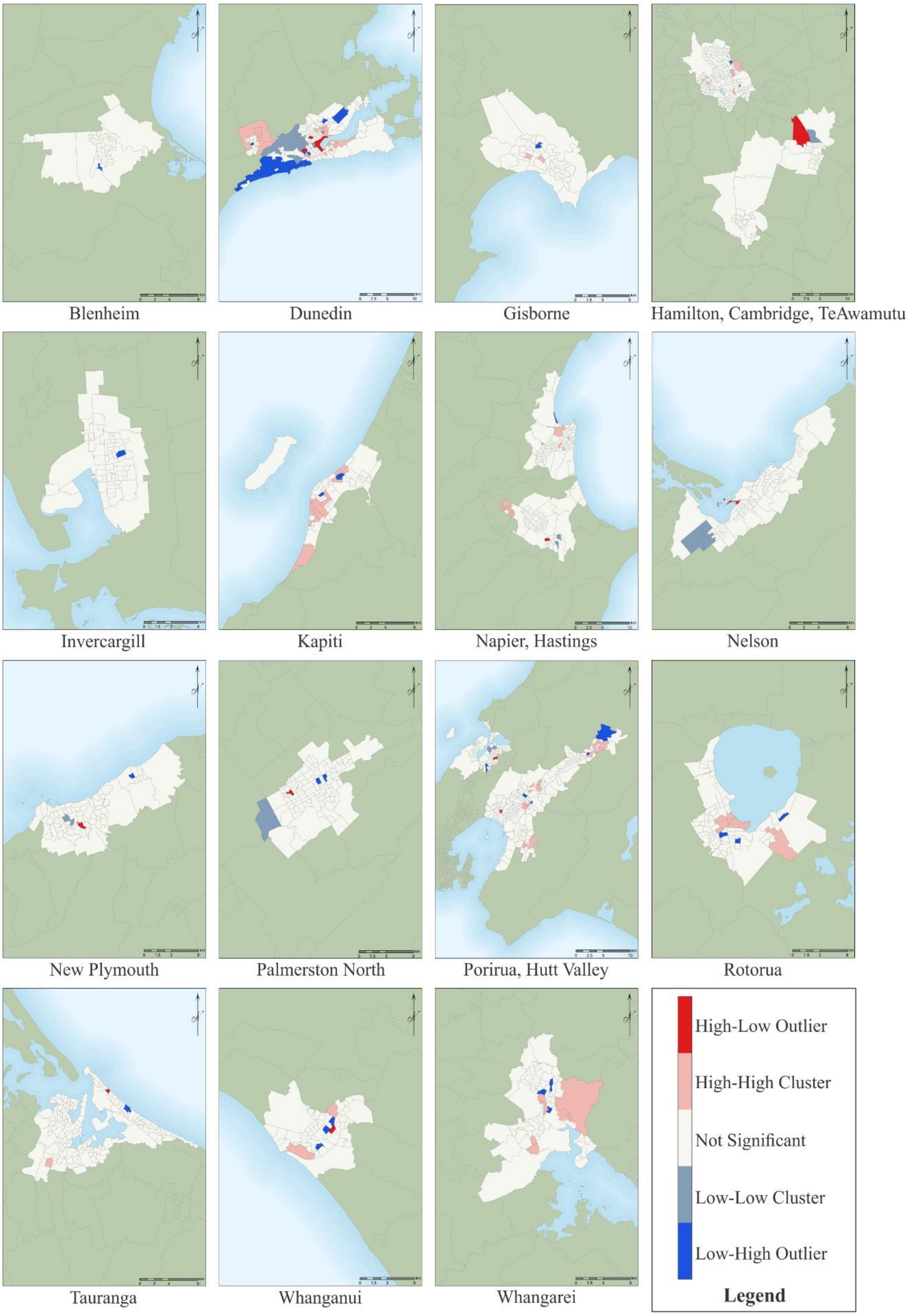

Figure E.30: *Other urban areas – Local spatial autocorrelation (2015/16 Rate per 1,000)*

Appendix E.32

Figure E.31: *Other urban areas – Local spatial autocorrelation (2015/16 SMR)*

Appendix E.33

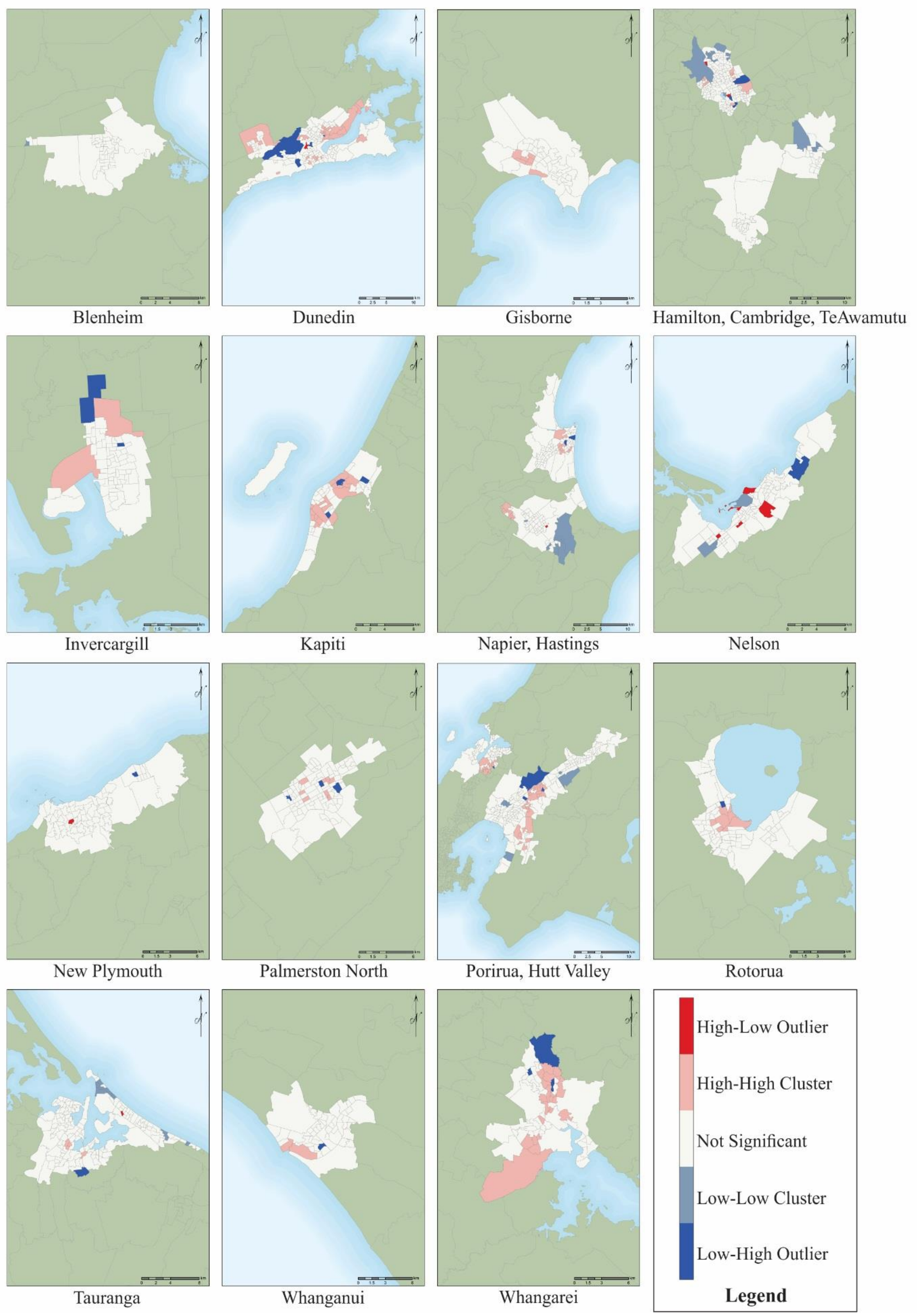

Figure E.32: *Other urban areas – Local spatial autocorrelation (2013/16 Rate per 1,000)*

Appendix E.34

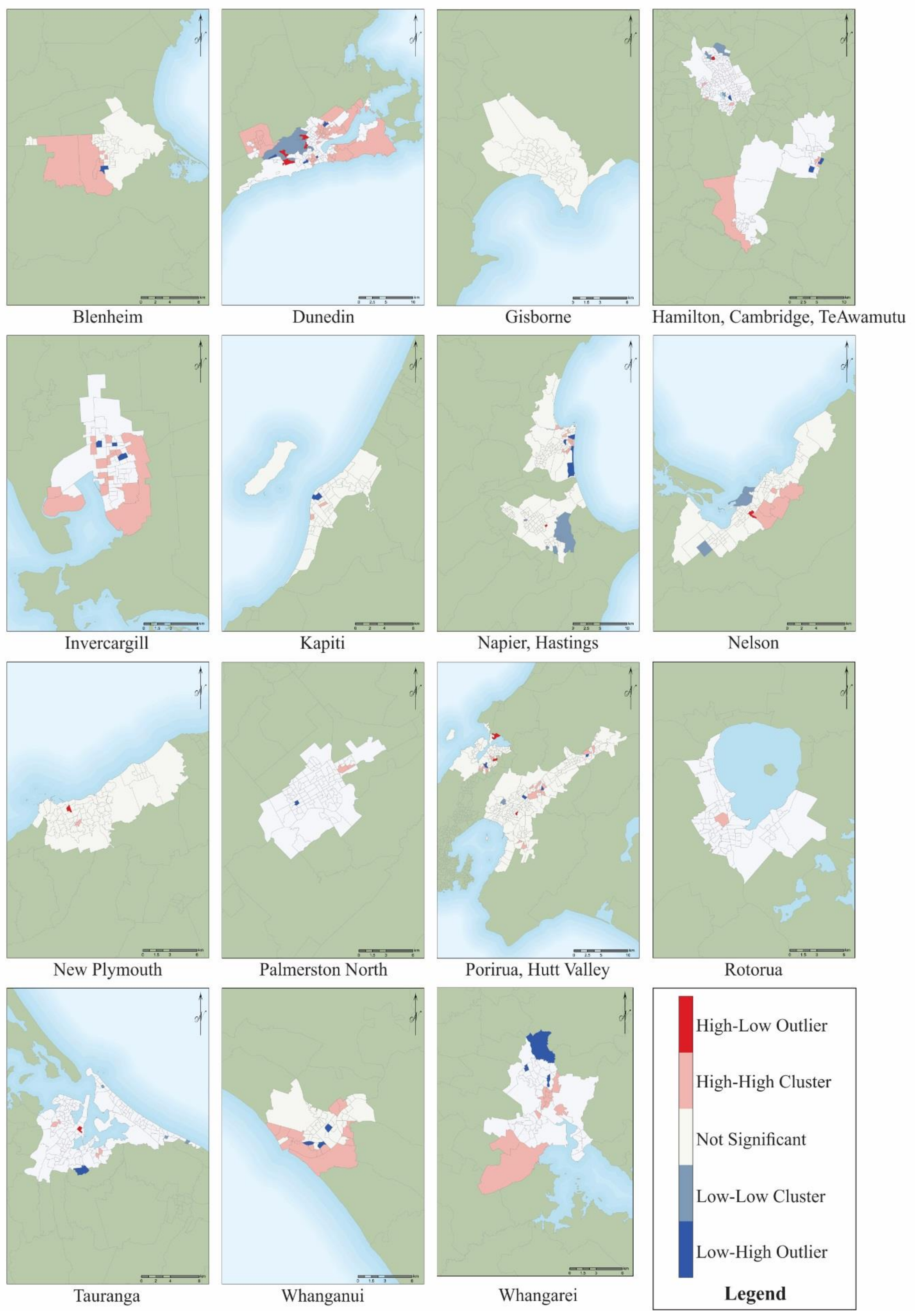

Figure E.33: *Other urban areas – Local spatial autocorrelation (2013/16 SMR)*

Appendix E.35

Table E.2: *Variance Inflation Factor results for multicollinearity from non-spatial models*

	Model						
	1	2	3	4	5	6	7
	E2SFCA	E800	E1600	E3000	N800	N1600	N3000
2013/14							
Fast Food	2.85	1.92	2.72	6.10	1.74	2.39	5.06
Takeaway	3.82	2.48	4.10	7.92	2.31	3.39	6.13
Dairy/Convenience	4.00	2.09	3.28	4.05	1.89	2.86	4.02
Supermarket	1.80	1.22	1.42	1.88	1.24	1.33	1.69
Fruit/Vegetable	1.70	1.17	1.35	1.64	1.18	1.33	1.53
Activity Facilities	2.37	1.39	1.84	2.49	1.32	1.59	2.19
Greenspace – Private	-	1.25	1.42	1.52	1.10	1.26	1.66
Greenspace – Public	-	1.09	1.13	1.12	1.04	1.12	1.32
2014/15							
Fast Food	2.94	1.79	2.68	6.23	1.73	2.26	5.12
Takeaway	4.08	2.48	4.19	8.51	2.08	3.44	6.62
Dairy/Convenience	4.13	2.19	3.62	4.08	1.85	2.98	4.09
Supermarket	1.85	1.22	1.43	1.85	1.23	1.36	1.74
Fruit/Vegetable	1.67	1.16	1.36	1.72	1.15	1.27	1.53
Activity Facilities	2.53	1.37	1.81	2.54	1.32	1.62	2.22
Greenspace – Private	-	1.24	1.41	1.52	1.10	1.25	1.63
Greenspace – Public	-	1.10	1.13	1.12	1.03	1.10	1.29
2015/16							
Fast Food	2.69	1.77	2.54	5.79	1.61	2.18	5.87
Takeaway	3.61	2.44	4.16	8.06	2.04	3.20	6.19
Dairy/Convenience	3.77	2.10	3.49	4.07	1.84	2.81	3.03
Supermarket	1.81	1.23	1.42	1.84	1.22	1.32	1.68
Fruit/Vegetable	1.65	1.15	1.36	1.69	1.14	1.27	1.49
Activity Facilities	2.28	1.33	1.81	2.57	1.22	1.55	2.22
Greenspace – Private	-	1.23	1.42	1.13	1.09	1.11	1.65
Greenspace – Public	-	1.10	1.13	1.07	1.03	1.07	1.32

All values given at 2 d.p.
E2SFCA: Enhanced Two-Step Floating Catchment Area
E: Euclidean-based buffer measures (in metres)
N: Network-based buffer measures (in metres)

Appendix E.36

Table E.3: *Geweke diagnostics from spatial regression models*

	Model						
	1	2	3	4	5	6	7
	E2SFCA	E800	E1600	E3000	N800	N1600	N3000
Intercept	1.4	0.1	-0.1	-0.7	0.5	-0.1	0.1
Fast Food	1.1	0.7	-0.3	0.7	0.7	0.5	0.1
Takeaway	-0.2	1.0	0.8	0.6	0.3	-1.3	-1.5
Dairy/Convenience	-1.4	-1.1	-0.6	1.7	-1.0	0.0	-0.4
Supermarket	-0.7	0.0	1.4	-0.5	1.2	0.1	-0.7
Fruit/Vegetable	0.5	-0.5	-1.8	1.3	-0.4	0.2	1.8
Activity Facilities	0.2	0.6	0.0	-1.4	0.0	0.2	1.2
Greenspace – Private	-	-0.6	0.1	0.4	-0.8	0.5	-0.2
Greenspace – Public	-	0.5	0.5	0.2	-0.2	0.9	0.5

All values given at 2 d.p.
E2SFCA: Enhanced Two-Step Floating Catchment Area
E: Euclidean-based buffer measures (in metres)
N: Network-based buffer measures (in metres)